Using RapidEye Satellite Imagery to Detect Forest Disturbances in British Columbia

by

John Thomas Te Reo Arnett

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Abstract

Improving our ability to track and monitor changes on Earth’s surface will inevitably enhance our ability to manage and monitor the biosphere. Remote Sensing technologies developed to monitor the Earth’s surface have already improved our understanding of dynamic land cover change at a variety of scales. Fundamental to the identification of land cover change is the detection of abrupt disturbance events. These events constitute direct changes to the composition and structure of ecological systems and may have long lasting effects. In a forestry context it is important to identify disturbances in a timely manner in order to inform management decisions.

The RapidEye constellation is a series of five identical Earth orbiting optical sensors capable of achieving five meter spatial resolution imagery with a daily return time. In this thesis we present two studies which assess the capacity of RapidEye to detect (1) stand replacing disturbances and (2) non-stand replacing disturbances in British Columbia.

In the first study we develop a robust method to identify stand-replacing disturbances across seven regions in British Columbia. Overall accuracy for the classification of forest disturbance ranged from 83.65 ± 0.77% to 97.65 ± 0.25% for individual 25 X 25 km test locations.

In the second study the utility of the RapidEye constellation to detect and characterize a low severity fire in a dry Western Canadian Forest was examined. Estimates of burn severity from field data were correlated with a selected suite of common spectral vegetation indices. All correlations between the ground estimates and vegetation indices produced significant results (p < 0.01). Consumption estimates of woody surface fuels ranged from 3.38 ± 1.03 Mg ha$^{-1}$ to 11.72 ± 1.84 Mg ha$^{-1}$ across four extrapolated severity classes.
The results of this thesis demonstrate the capacity of the RapidEye constellation to accurately detect stand replacing and non-stand replacing disturbances. We conclude by recommending the use of RapidEye to assess forest disturbances, with an emphasis on the spatial detail and temporal availability of imagery captured by the RapidEye sensors.
Preface

This thesis is the combined work of two scientific papers of which I am the lead author. I preformed the primary research, data analysis, interpretation of the results and prepared the final manuscripts. Dr. Nicholas Coops project oversight as well as editorial assistance. Dr. Sarah Gergel provided guidance on ecological principals and statistical approaches. Dr. Robert Falls provided insight into the practical application of the research as well as editorial assistance. Dr. Lori Daniels provided guidance on ecological principals and fire ecology. Russell Baker provided guidance on the practical and applied aspects of the research.

Publications resulting from this thesis thus far include (reprinted with permission of the publishers):

A Version of Chapter 2 has been published in:


A Version of Chapter 3 has been submitted for publication in:

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Finally I would like to thanks the IRSS lab -I’m sure you’ve all helped me at some point along the way!
I dedicate this thesis to my parents Barb and Chris Arnett for their support, my Grandparents John and Norma Arnett getting me there, and my Grandma Judy Anderson for getting me started.
1. INTRODUCTION

Identifying forest disturbances is a fundamental objective of forest management. Disturbance events are key drivers of forest structure, function, and composition (Franklin et al., 2002) and occur throughout a range of temporal and spatial scales. Globally, forest disturbances may have cumulative effects on species diversity and distribution (Defries et al. 1999, Gutschick and Bassirirad 2003, Loboda et al. 2012) as well as geophysical and landscape processes (e.g. Sidle 1992, Samonil et al. 2010, Pohl et al. 2012). Disturbance may also affect climate through structural and biochemical changes of forest vegetation; this can include change in land use and cover, surface albedo (e.g. Davin and de Noblet-Ducoudré 2010), evapotranspiration (Maness et al. 2013), and carbon flux (Kurz and Apps 1999). Consistent and timely identification of forest disturbances offers many benefits to managers and stakeholders concerned with monitoring various forest attributes.

Sustainable forest management often relies on the ‘natural range of variability’ (NRV) concept as a fundamental guide to managing disturbance (Landres et al. 1999). Within the proposed NRV, persistent small-scale disturbances are important for the maintenance of diverse habitat types and eventually contribute to the complexity of old-growth forest types (Oliver 1980). Emerging understanding of fine-scale disturbances suggests that low frequency, spatially discrete disturbances contribute to the maintenance of biodiversity (e.g. Picket and White 1985). Disturbances encompassed by the NRV are typically non-catastrophic in scale and tend to present a ‘no net loss’ scenario with respect to forest biomass and biodiversity. For the purpose of this research we refer to these as ‘non-stand replacing disturbances’.
Anthropogenic agents are arguably the main drivers of forest disturbance in many areas on Earth (Vistosek 1997, Marsh and Grossa 1996). Unlike disturbances encompassed by the NRV, anthropogenic disturbance events often result in permanent changes to the landscape (Foster 1992, Franklin et al. 2002). Furthermore anthropogenic disturbances tend to exceed the frequency and intensity of those occurring within the NRV. For example, Pearson (2010) found that during a 140-year period the extent of areas affected by logging was ten times that of disturbances attributed to non-anthropogenic agents. Anthropogenic disturbances such as harvest and land conversion are often abrupt, directly changing structural aspects of forests (Franklin et al. 2002). Although forest management paradigms have begun to emulate natural disturbance as a component of management practice, clear-cutting is nonetheless a common method of forest harvest (Bouchard et al. 2008).

Globally, the cumulative contribution of ecological services (such as maintenance of a suitable climate and biodiversity) may fluctuate in response to changes in the forest disturbance regime (Davin and de Noblet-Ducoudré 2010, Sunderlin et al. 2005). Changes to natural disturbance regimes may have undesirable consequences for people that rely on the ecological services provided by forests (e.g. Maruyama and Morioka 1998, Vedeld et al. 2007). Concerns over forest disturbance at a variety of scales have led to initiatives aimed at monitoring the Earth’s 3.8 billion hectares of forest area (FAO 2012). Programmes such as the United Nations Framework Convention on Climate Change (UNFCCC) and Reducing Emissions from Deforestation and Forest Degradation (REDD+) aim to reward the conservation of forests through the payment for ecological services (PES) by large carbon emitters (e.g. Mahanty et al. 2013). Identification of key disturbances is crucial for adopting management strategies best suited to meet the needs of a particular region. Attributes such as disturbance type, extent, and duration are all important...
considerations for government and stakeholders wishing to assess and manage disturbances (e.g. Coops et al. 2009). Timely, cost effective monitoring of disturbances across large areas is best achieved through the implementation of remote sensing technologies.

Remote sensing has aided implementation of forest disturbance monitoring initiatives (Cohen et al. 1996, Rogan and Miller 2006). For example, Brazil’s PRODES project, aimed at mapping annual deforestation in the Amazon, collects monthly data on abrupt changes in forest cover to estimate deforestation (Shimabukuro et al. 2006). The PRODES programme has been widely successful despite the relatively coarse grain size of 25 ha. Initiatives such as REDD+ have begun to develop global frameworks for assessment of anthropogenic disturbances and deforestation. The REDD+ initiative, aimed primarily at tropical forests located in developing countries, attempts to reward nations based on their ability to maintain the integrity of local forests (Miles and Kapos 2008, Pistorius 2012). Penman et al. (2003) suggest that monitoring for REDD+ must include (1) spatial extent of deforested area and (2) estimates of carbon stock densities, in order successfully address management concerns.

In Canada, the Canadian Forest Service’s National Forest Carbon Monitoring initiative (NFCM) was developed to meet the 1997 Kyoto protocol’s concerns over carbon uptake. The NFCM utilizes spatial forest inventory data collected at the national, provincial/regional, operational, and stand level to model deforestation, afforestation, and reforestation over the entire country (Kurz and Apps 2006). Currently, spatial aggregation of disturbance within the NFCM bounds is generated from aerial photography and remote sensing.

British Columbia is an ideal location to develop remote sensing technologies aimed at monitoring and tracking forest disturbances. In British Columbia, an economic reliance on forest
products has helped foster some of the world’s most comprehensive forest practices. As part of their commitment to monitoring forest resources, British Columbia’s Ministry of Forests, Lands and Natural Resources Operations (FLNRO) maintains a relatively comprehensive forest inventory database. Spatial data pertaining to disturbance type, forests management unit, harvest activity, and species composition are included in the inventory, which is derived from a combination of aerial photography and interpretation, as well as field observations. Three characteristics make the Province particularly suitable to conduct remote sensing disturbance research. These are summarized as follows:

1. The Province contains a variety of diverse forest types
2. The Province is host to a large range of forest disturbances types occurring at multiple spatial and temporal scales
3. The Provincial government arguably maintains an extensive and detailed forest inventory which could be used to test and calibrate disturbance detection routines

1.1 Remote Sensing

Remote sensing is increasingly used to assess ecological change and thus has become a key data source for forest and land managers (Joseph et al. 2010). Remotely sensed imagery can provide a suite of information pertaining to forest characteristics and spatial attributes of vegetation cover (Wulder and Franklin 2007). Furthermore remote sensing provides valuable information for ecological monitoring and is a cost-effective alternative to field and aerial surveys (e.g. Mumby et al. 1999).

Earth observing missions such as the National Aeronautics and Space Administration’s (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) and National Oceanic and
Atmospheric Administration’s (NOAA) Advanced Very High Resolution Radiometer (AVHRR) offer long-term continual data archives with applications in global forest monitoring. These satellites carry sensors directed at capturing Earth surface phenomena encompassing a range of spatial, temporal, radiometric, and spectral resolutions. Table 1.1 reviews some contemporary satellite sensors commonly used for earth surface observations.

**Table 1.1** An overview of different remote sensing platforms and resolutions. *MS = multispectral, *SWIR = shortwave infrared, pan = panchromatic

<table>
<thead>
<tr>
<th>SATELLITE (SENSOR)</th>
<th>SWATH WIDTH (km)</th>
<th>SPATIAL RESOLUTION (m) (*)</th>
<th>SPECTRAL RESOLUTION (nm)</th>
<th>POSSIBLE APPLICATIONS</th>
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<td><strong>LOW SPATIAL RESOLUTION SENSORS</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NOAA (AVHRR)</td>
<td>3000</td>
<td>1100</td>
<td>500-1250</td>
<td>Regional Forest Cover (Patopov et al. 2011)</td>
</tr>
<tr>
<td>ENVISAT (MERIS)</td>
<td>1150</td>
<td>300-1200</td>
<td>390-1040</td>
<td>Oceanic productivity (Moore et al. 2012)</td>
</tr>
<tr>
<td>Terra/Aqua (MODIS)</td>
<td>2330</td>
<td>250-1000</td>
<td>366-14385</td>
<td>Global fire occurrence (Hantson et al. 2013)</td>
</tr>
<tr>
<td>SeaStar (SeaWiFS)</td>
<td>1500</td>
<td>1100</td>
<td>402-885</td>
<td>Oceanic Observations (Karabashev and Evdoshenko 2013)</td>
</tr>
<tr>
<td><strong>MEDIUM SPATIAL RESOLUTION SENSORS</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Landsat 5,7,8 (TM, ETM+, OLI)</td>
<td>185</td>
<td>30</td>
<td>450-2350</td>
<td>Large area land cover mapping (Wulder et al. 2008)</td>
</tr>
<tr>
<td>SPOT 5 (HRG)</td>
<td>60</td>
<td>10 (MS); 20 (SWIR)</td>
<td>500-1730</td>
<td>Terrain Mapping (Wallerman et al. 2010)</td>
</tr>
<tr>
<td>EO-1 (HYPERION)</td>
<td>7.5</td>
<td>30</td>
<td>400-2500</td>
<td>Coastal classification</td>
</tr>
</tbody>
</table>
Until recently, most satellites providing publicly available data offered imagery of relatively low spatial and temporal resolution (Fensholt et al. 2011). Higher spatial resolution platforms such as Ikonos and Quickbird sensors are capable of resolving fine scale land cover patterns; however, these sensors are limited in swath width and temporal resolution, and are generally considered expensive on an area basis. High temporal resolution sensors such as MODIS are capable of a two-day return time; however, its 250-meter grain size is unable to resolve smaller scale disturbance and land change events (Townsend and Justice 1988). Similarly, AVHRR offers a global revisit time every six hours but provides a coarse spatial resolution of 1.09 km/pixel (at nadir).

Both AVHRR and MODIS have been used to produce maps depicting changes in global forest cover for over a decade; however, their relatively low spatial resolution makes these sensors less useful for mapping change at the local or regional scale. Local mapping of forest is typically carried out using the NASA’s Landsat sensor (Cohen et al. 2002). Landsat data has been largely successful in assessing land cover trends over large areas and relatively long temporal intervals; however, with a 30-m resolution and 16-day return time, Landsat may be unable to resolve important abrupt or fine-scale changes (e.g. Gong and Xu 2003, Xie et al. 2008), especially in

<table>
<thead>
<tr>
<th>HIGH SPATIAL RESOLUTION SENSORS</th>
<th>16.8</th>
<th>2.44 (MS); 0.8 (pan)</th>
<th>450-900</th>
<th>Disaster response (Meslem et al. 2011)</th>
</tr>
</thead>
<tbody>
<tr>
<td>QuickBird-2</td>
<td>13.8</td>
<td>4 (MS); 1 (pan)</td>
<td>450-850</td>
<td>Urban planning/mapping (Tack et al. 2012)</td>
</tr>
<tr>
<td>IKONOS</td>
<td>77</td>
<td>6.5 (MS)</td>
<td>440-850</td>
<td>Agricultural monitoring (Tapsall et al. 2010)</td>
</tr>
<tr>
<td>RapidEye</td>
<td>18.5</td>
<td>3.5 (MS)</td>
<td>450-900</td>
<td>Urban planning/mapping (Tack et al. 2012)</td>
</tr>
</tbody>
</table>
areas with persistent cloud cover. This time delay can mean that events such as forest fires, illegal harvesting, and insect infestation may have long since occurred before they are identified using satellite imagery.

A study using Landsat images gathered over a 29-year period in the Brazilian Cerrado region concluded that the probability of acquiring a cloud free image during the wet season was <10% (Sano et al. 2007). A similar study conducted by Asner (2001) found that the probability of acquiring a cloud-free image of the northern Amazon was nearly zero for any given season. Although these studies are presented in a Brazilian context, global cloud cover maps developed by the University of Manitoba suggest that Brazilian annual cloud cover is comparable to the west coast of North America (Anderson 2014). Landsat’s 16-day return interval allows for a maximum of 22 images to be acquired over the same area in a given year. An increase in the temporal frequency at which images are recorded would increase the probability of achieving cloud free scenes necessary for detection of abrupt changes in land cover.

Recent advancements in remote sensing technologies have attempted to solve dilemmas surrounding the spatial and temporal limitations of older remote sensing platforms. Satellite constellations composed of multiple sensors can improve temporal coverage while maintaining finer spatial resolution. The RapidEye Constellation (RapidEye) is a network of five identical satellites working in unison to capture 5-meter multispectral resolution imagery with a 1-day return interval over most areas of Earth. RapidEye’s ability to combine attributes of high spatial and temporal resolution sensors make it unique amongst other Earth observation platforms. Automating basic change detection procedures using RapidEye could provide stakeholders with a framework to routinely and rapidly identify land cover change and disturbances across large areas with minimal user intervention.
1.2 Thesis Objectives

This thesis consists of two main objectives. The first is to develop a robust routine for detecting stand-replacing disturbances in British Columbia using high-spatial and temporal resolution RapidEye remote sensing imagery. The second objective is to assess the capacity of RapidEye to map and evaluate less severe, smaller, non-stand replacing disturbances. To achieve these objectives four research questions have been proposed:

1. Can a modified disturbance index be derived from imagery of British Columbian forests provided by the RapidEye sensor?

2. How accurately can we identify stand-replacing disturbances from areas containing a high level of recent forest disturbances in British Columbia?

3. Can we use RapidEye to assess stand damage caused by a low severity fire in a dry Western Canadian forest?

4. How well can vegetation indices derived from RapidEye correlate with ground measures of burn severity — and how do these measures compare to indices derived from conventional Landsat imagery?

Chapter 2 derives a modified disturbance index using RapidEye imagery based on the methods of Healey et al. (2005). In this study a tasselled cap transformation (TCT) is derived from RapidEye imagery using forested regions across British Columbia. Components of the TCT are used to derive a disturbance index which is then assessed on its ability to delineate stand-replacing disturbance from seven 625 km$^2$ RapidEye tiles. The accuracy of the modified disturbance index is tested using Provincial forest inventory data from manually verified ground locations.
Chapter 3 evaluates the ability of RapidEye to detect fine-scale forest damage associated with a non-stand-replacing fire in a dry Western Canadian forest. This study makes use of detailed ground data, which is used to assess stand damage on a tree-by-tree basis. Estimates of tree damage are correlated with conventional vegetation indices derived from RapidEye, Landsat TM, and Landsat OLI. Three commonly used aspects of imagery associated with the detection of disturbance are explored. Firstly, metrics of semi-variance are assessed and interpreted to provide an indication of the level of detail provided by the imagery from both sensors. Secondly, several common vegetation indices are correlated with tree damage on pixel-by-pixel basis. Finally, the consumption of woody surface fuel by fire is estimated using the magnitude of change detected by the sensors.

Finally Chapter 4 provides a synthesis of the overall research, a summary of the two studies, and provides guidance for future research.

The remainder of Chapter 1(section 1.3) describes the technical components of the RapidEye Constellation as well as change detection techniques explored in Chapters 2 and 3.

1.3 Remote Sensing of Disturbance

1.3.1 Sensor Development

The RapidEye constellation was originally proposed in 1996 as a means of providing frequent multispectral imagery to augment a variety of Earth observing applications, including the monitoring of agricultural, forestry, disturbances, and natural disasters. The constellation was launched in 2008 and began providing commercial imagery in early 2009. The RapidEye mission has been designed to last at least seven years.
The RapidEye constellation is comprised of five sun-synchronous satellites orbiting the Earth at an altitude of 630 km. Each satellite carries an identical pushbroom scanner capturing multispectral imagery at a spatial resolution of 6.5 meters (at nadir). Imagery provided by RapidEye undergoes routine radiometric calibration to provide interchangeable imagery amongst the other sensors (Naughton et al. 2011). The RapidEye sensors are able to capture imagery covering approximately 5 million km$^2$ of the Earth in a 24 hour period, as well as a daily return time (off-nadir) and a 5.5-day return time at nadir. Each sensor stores imagery onboard until the satellite passes the receiving station in Svalbard, Norway. RapidEye’s five band multispectral configuration, which includes a unique red-edge band, makes it an ideal platform for vegetation monitoring (Bindel 2011). In addition RapidEye’s high frequency return time allows for much more subtle changes in land cover to be detected, however, in order for these changes to be detected images must undergo substantial processing. Table 1.2 modified from Tyc et al. (2005) provides a summary of RapidEye’s spectral band configuration.

<table>
<thead>
<tr>
<th>Band</th>
<th>Description</th>
<th>Spectral range (nm)</th>
<th>Specified center wavelength (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Blue</td>
<td>440–510</td>
<td>475.0</td>
</tr>
<tr>
<td>2</td>
<td>Green</td>
<td>520–590</td>
<td>555.0</td>
</tr>
<tr>
<td>3</td>
<td>Red</td>
<td>630–685</td>
<td>657.5</td>
</tr>
<tr>
<td>4</td>
<td>Red-edge</td>
<td>690–730</td>
<td>710.0</td>
</tr>
<tr>
<td>5</td>
<td>NIR</td>
<td>760–850</td>
<td>805.0</td>
</tr>
</tbody>
</table>

Table 1.3 provides a summary of existing studies where RapidEye has been implemented as a successful remote sensing platform.
<table>
<thead>
<tr>
<th>Application</th>
<th>Findings</th>
<th>Benefits</th>
<th>Author</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satellite image calibration</td>
<td>RapidEye sensor measures radiance within 4% of predicted values</td>
<td>RapidEye sensor demonstrated to provide precise radiometric resolution</td>
<td>Naughton et al. (2011)</td>
</tr>
<tr>
<td>Agricultural Crop Monitoring</td>
<td>Mapping agricultural land cover</td>
<td>Potential for improved crop monitoring</td>
<td>Tapsall et al. (2010)</td>
</tr>
<tr>
<td>Ecosystem Classification</td>
<td>Combined results of red-edge and NIR bands may be used for increase accuracy for separation vegetation classes</td>
<td>Improved mapping for conservation and ecological classification</td>
<td>Bindel and Hese (2011)</td>
</tr>
<tr>
<td>Grassland Monitoring</td>
<td>Differences among grassland habitats</td>
<td>Additional data for spatial habitat modeling</td>
<td>Franke et al. (2012)</td>
</tr>
</tbody>
</table>

RapidEye imagery is available through BlackBridge, which owns and operates the RapidEye constellation. Commercial imagery is readily available through BlackBridge’s web-based ‘EyeFind’ tool where specific orders can be queried by entering known coordinates, selecting a specific tile of interest, or by uploading a KML, KMZ or SHP file. Processed imagery is available in either geometrically uncorrected, or as an orthorectified tile product.

1.3.2 Multispectral Vegetation Indices

Simplification of multiband remote sensed data into interpretable indices allows powerful conclusions to be made regarding vegetation condition (Jackson and Huete 1991). By performing various arithmetic operations on pixel reflectance values we can derive indices that may be more useful for assessing and quantifying Earth surface phenomena than simply using the original bands. The Normalized Difference Vegetation Index (NDVI) is one such index commonly derived from remote sensed data. The NDVI takes advantage of a large increase in reflectance...
between the visible red and NIR wavelengths as exhibited by healthy vegetation. Other indices, such as the enhanced vegetation index (EVI), the soil adjusted vegetation index (SAVI), the normalized burn ratio (NBR) also take advantage of similar differences in wavelengths reflected by vegetation. Table 1.4 provides a summary of common derived vegetation indices.

Table 1.4 describes commonly used vegetation indices

<table>
<thead>
<tr>
<th>Indices Used</th>
<th>Formula</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enhanced Vegetation Index (EVI)</td>
<td>(2.5 \times \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + 6 \times \text{Red} - 7.5 \times \text{Blue} + 1)})</td>
<td>Gao et al. (2000)</td>
</tr>
<tr>
<td>Normalized Difference Vegetation index (NDVI)</td>
<td>(\frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}})</td>
<td>Tucker (1979)</td>
</tr>
<tr>
<td>Soil Adjusted Vegetation Index (SAVI)</td>
<td>([\frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red} + 0.5}] \times (1 + 0.5))</td>
<td>Huete (1988)</td>
</tr>
<tr>
<td>Normalized Burn Ratio (NBR)</td>
<td>(\frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}})</td>
<td>Key and Benson (1999)</td>
</tr>
<tr>
<td>Normalized Difference Moisture Index (NDMI)</td>
<td>(\frac{\text{NIR} - \text{MIR}}{\text{NIR} + \text{MIR}})</td>
<td>Wilson and Sader (2002)</td>
</tr>
<tr>
<td>Tasseled Cap Transform 1 (TC1)</td>
<td>Linear weighting of all bands emphasizing overall pixel brightness (depends on sensor)</td>
<td>Originally described by Kauth and Thomas (1976)</td>
</tr>
<tr>
<td>Tasseled Cap Transform 2 (TC2)</td>
<td>Linear weighting of all bands emphasizing differences between NIR and RED wavelengths (depends on sensor)</td>
<td>Originally described by Kauth and Thomas (1976)</td>
</tr>
<tr>
<td>Tasseled Cap Transform 3 (TC3)</td>
<td>Linear weighting of all bands (depends on sensor)</td>
<td>Originally described by Kauth and Thomas (1976)</td>
</tr>
</tbody>
</table>

Another set of indices commonly used in image processing are the indices derived from the Tasseled Cap Transformation (TCT) (Kauth and Thomas 1976, Crist and Kauth 1986, Horne 2003). The TCT calculates linear uncorrelated combinations of bands, reducing redundancy in the data; typically undertaken using principal components analysis. Originally developed for the
four Landsat MSS bands (Kauth and Thomas 1976), TCTs have since been produced for many other sensors such as Landsat Thematic Mapper (TM), ASTER, Ikonos, and Quickbird (Yarbrough et al. 2005, Horne 2003). The original TCT developed for Landsat MSS described two main indices: brightness and greenness, as well as a third “yellowness”; however the addition of shortwave infrared (SWIR) band on Landsat TM (as well as additional spectral bands) allowed a third ‘wetness’ index to be interpreted (Healey et al. 2005). As part of the processing of the RapidEye data, a sub-objective of this research will be to derive a TCT for RapidEye. The TCT has been shown to be more successful at detecting change between image dates than the NDVI as it is derived from all spectral bands and allows a comparison of both changes in the greenness and the overall brightness spectral responses (Healey et al. 2005).

1.3.3 Change Detection Techniques
Assessment of ground cover change from remotely sensed imagery typically relies on identification of changed areas from images collected on two or more dates (Coppin et al. 2004). Techniques for identifying change within digital imagery have been developed within the disciplines of remote sensing, photogrammetry, computer vision, and image processing. Singh (1989) defines change detection as the identification of difference in an objects state by observing it at different times. Lu et al. (2004) and Singh (1989) provide comprehensive reviews of change detection using remote sensing beyond the scope of this thesis. Prior to implementation of successful change detection various stages of preprocessing must first be applied to satellite data. (1) Geometric fidelity is a major consideration of change detection; this implies that images pixels within multitemporal will be co-registered to the same geographic location. (2) DN numbers of similar feature must be represented by similar values across images -this done through radiometric normalization of the images during preprocessing stages.
Once the selected imagery has been radiometrically and geometrically corrected a number of change detection techniques can be applied to extract and map regions of change. Two basic categories of change detection exist in the literature; these are (1) classification based and (2) radiometric based approaches (Johnson and Kasischke 1998). Classification based approaches rely on delineating land cover classes then spatially assessing how these classes have changed over time. The second radiometric based approach assesses the magnitude of radiometric change between corresponding image pixels. Perhaps the most basic method of radiometric change detection involves image differencing; a process where pixel values from one image are subtracted from that of another, as follows:

$$T_1 - T_2 = T_{\text{Difference}}$$

Where $T_1$ is the first image and $T_2$ represents the second image in a stack; the result is known as a difference image. In an $n$-band image a simple image differencing will result in $n$-bands representing vectors of change. Change can be attributed to the difference image by setting thresholds for pixels constituting change, or by using a probability distribution (Singh 1989). Indices derived from linear combinations of band values may also be used in more robust methods of change detection (Lyon et al. 1998). The utilization of vegetation indices, or transformed band differencing, relies on the derivation of vegetation indices, which are then differenced to produce a change map (e.g. Nelson 1983).

The disturbance index (DI) proposed by Healey et al. (2005) is a method of transformed band differencing that was developed to be specifically sensitive to loss of forest vegetation. This approach takes advantage of linear combinations of Landsat TM or ETM+ bands resulting in a single band image. The single band image for one date can be subtracted from another to
produce a bi-temporal difference image, depicting disturbances. Healy et al.’s (2005) DI is
summarized as follows:

\[
DI_{difference} = [B_{T1} - (G_{T1} + W_{T1})] - [B_{T2} - (G_{T2} + W_{T2})]
\]

where B, G, and W, represent Landsat Brightness, Greenness, and Wetness values. A threshold
for extracting areas of change can then be applied to the single band DI. Healey et al. (2005)
suggest using an arbitrary value of ‘2’ to discriminate between disturbed and no change pixels.

More complex statistical procedures such as multivariate alteration detection (MAD) (Canty and
Nielsen 2008) rely on information derived from the covariance matrices of from both images to
identify change. The MAD procedure used by Canty and Neilsen (2008) may also be used as a
means of radiometric normalization for two or more images.

1.4 Significance of Research

Remote sensing provides a cost-effective, viable solution to begin to assess a multitude of
metrics associated with forest disturbance and mapping. In order to better understand the
dynamic state of the world’s forests, improve inventory assessments, and provide better
information to managers and policy makers it is necessary to provide up-to-date and detailed
products derived from satellite imagery. RapidEye and other constellations can potentially
provide a solution to regional and local scale disturbance monitoring needs due to the sensors
fine spatial and temporal resolutions and their ability to recapture imagery at frequent intervals.

By providing tools and methods to support the need of annual disturbance detection this project
will contribute to large-scale mapping frameworks to assess changes in forested ecosystems. The
results of this study will be especially pertinent to regions that may lack sufficient resources and infrastructure to monitor forest disturbances.
2 DETECTING STAND REPLACING DISTURBANCE USING RAPIDEYE IMAGERY: A TASSELED CAP TRANSFORMATION AND MODIFIED DISTURBANCE INDEX

2.1 1Introduction

Understanding changes in vegetated land cover is a central objective in the sustainable management of forests and is vital in developing effective forest policies (Pitt and Pineau 2009). Currently, much of the information used to assess land cover change is generated through optical remote sensing platforms or through the interpretation of aerial photography (Rogan and Miller 2006). Monitoring land cover change using remote sensing consists of three distinct categories. These are summarized by Verbesselt et al. (2012) as (1) seasonal changes associated with vegetation phenology and climate, (2) gradual changes or trends in ecosystems, and (3) abrupt or immediate disturbances.

Abrupt disturbance events such as those caused by fire, harvest, and flooding, are key drivers of forest structure, function, and composition (Franklin et al. 2002). These events constitute perturbations to the normal state of an ecosystem relative to the spatial and temporal scale at which that particular ecosystem is studied (Picket and White 1985). Disturbances occur globally at a range of spatial scales and may have cumulative effects on species diversity and distribution (Defries et al. 1999; Gutschick and Bassirirad, 2003; Loboda et al. 2012) as well as geophysical and landscape processes (e.g., Sidle, 1992; Samonil et al. 2010; Pohl et al. 2012). Disturbance events also affect climate through structural and biochemical changes of forest vegetation. These

can include changes in land use and cover, surface albedo (e.g., Davin and de Noblet-Ducoudré, 2010), evapotranspiration (Maness et al. 2013), and carbon flux (Kurz and Apps 1999). Although abrupt disturbance events occur under natural conditions, the rate at which they occur tends to be intensified by human activity (Pearson 2010; Vistosek et al. 1997). Additionally many disturbances are often small and scattered; requiring detailed spatial information for their identification (Townshend and Justice 1988).

Consistent and timely identification of forest disturbances offers many benefits to managers and stakeholders concerned with monitoring various forest attributes. However, feasible and timely monitoring of forest disturbance over large areas is only achievable through the use of remote sensing platforms (e.g., Kerr and Ostrovsky 2003). The ability to automate or semi-automate detection of abrupt disturbances across the landscape can provide vital information to compliment forest inventories at a range of administrative levels.

A variety of methods exist for the detection of change within satellite imagery. Coppin et al. (2004) provides an overview of nine distinct methods of change detection using data derived from remotely sensed imagery. One of the simplest and most widely used methods is univariate image differencing, a process whereby pixel values from one image date are subtracted from that of another coregistered image from another image date. The resulting image depicts changes that have occurred between image acquisition times. A simple threshold can be applied to the univariate difference image whereby values above the threshold can be attributed to change. Univariate image differencing is commonly applied to transformed data such as vegetation indices (e.g., Lyon et al. 1998; Lu et al. 2004).
A commonly used set of vegetation indices is the Tasseled Cap Transformation (TCT). The TCT derives new linear uncorrelated combinations of bands, typically using principle components analysis (PCA), which reduces redundancy in the dataset (Yarbrough et al. 2005). Originally derived using the four Landsat Multispectral Scanner (MSS) bands (Kauth and Thomas 1976), TCT transformations have been calculated for ASTER, IKONOS, and Quickbird data (Yarbrough et al. 2005; Horne 2003). The original TCT described the three indices, ‘brightness’, ‘greenness’ and ‘yellowness’ (Kauth and Thomas 1976); however the addition of shortwave infrared (SWIR) band on Landsat TM allowed for the third index to be interpreted as ‘wetness’ (Healey et al. 2005).

While the use of remote sensing data to monitor disturbance has been successful in identifying and mapping disturbances at a range of scales (Coppin and Bauer 1996), consistent frameworks aimed at ongoing monitoring of forest disturbance are limited (Mayaux et al. 2005; Xin et al. 2013). Monitoring forests using remote sensing often results in a compromise between high spatial and temporal resolution imagery, with high temporal resolution imagery often being limited to coarse spatial resolutions and fine spatial resolution imagery limited by swath width and sensor return time (Chambers et al. 2007). The Landsat series is arguably the most frequently used remote sensing platform (Wulder et al. 2012), however with 30 m spatial resolution and a 16 day return time, Landsat may miss important change events, especially in areas where cloud obscuration is common (Asner 2001; Sano et al. 2007). Increasing the return time of a satellite sensor inherently increases the probability of acquiring cloud-free imagery; however, many high-temporal resolution sensors such as the Advanced Very High Resolution Radiometer (AVHRR), and the Moderate Imaging Spectrometer (MODIS), are limited to spatial resolutions of 1 x 1 km and 250 X 250 m respectively and may not be suitable for monitoring and
mapping local and regional forest disturbances. Frequently updated mapping of disturbance is fundamental to any forest inventory; however, achieving an appropriate balance between the spatial and temporal resolutions of a sensor remains a challenge.

Satellite constellations can potentially provide a solution to the spatial/temporal compromise associated with other sensors. For example, a collaborative effort between the United Kingdom, Algeria, Nigeria, Thailand, and Turkey has led to the creation of the Disaster Monitoring Constellation (DMC). The DMC constellation is a series of satellites with sensors acquiring data comparable to imagery produced from the Landsat red, green, and near-infrared (NIR) bands, however the constellation design and wider swath width allows for daily coverage (da Silva-Curiel et al. 2005). The success of the DMC constellation has led to a second generation of DMC satellites launched between 2005 and 2011. The commercially operational RapidEye is another constellation platform that makes use of five identical sensors to provide 5 X 5 m spatial resolution imagery with a daily time of 5.5 days at nadir (daily if considering off-nadir imagery). The RapidEye sensors consist of five bands situated in the visible and NIR portions of the electromagnetic spectrum with a range of 440-850 nm. Cross calibration studies have shown individual RapidEye sensors to be interchangeable, with recorded radiometric differences within 2% amongst sensors (Thiele et al. 2012). RapidEye’s spectral band configuration is ideal for vegetation and ecological monitoring (Bindel et al. 2011), while the temporal coverage may be useful for natural disaster monitoring (Metternicht et al. 2005).

In this paper we investigate the detection of stand-level disturbances in annual and bi-annual forest cover in British Columbia, Canada. British Columbia (BC) is a key forested area in Canada and encompasses many climatic gradients and forest types. We use provincial forest inventory data to identify calibration and validation sites to assess disturbance throughout the
province. We then derive a set of indices using RapidEye 5 band data to develop a ‘disturbance index’, using the TCT following methods originally proposed by Healey et al. (2005) and assess its accuracy using conventional forest inventory polygons and visual interpretation approaches.

2.2 Methods

For our purpose, BC is an ideal region to study forest change. In BC a gradient of forest types exist, ranging from wet temperate rainforests along coastal regions to dry mixed grassland forests in the southern interior. In addition, detailed forest inventory data is routinely collected by the BC Ministry of Forests, Lands and Natural Resources Operations (MoFLNRO). Forest inventory layers catalogued by the MoFLNRO provided valuable information on the location and date of the disturbances being studied.

The RapidEye constellation consists of five identical sensors employed to deliver a resampled 5 X 5 m spatial resolution product. The radiometric resolution of RapidEye imagery is provided in a 16-bit range representing scaled radiance values. RapidEye bands are located in the blue, green, red, red edge, and NIR regions of the electromagnetic spectrum, with respective wavelength ranges at 440–510 nm, 520 – 590 nm, 630 – 685 nm, 690 – 730 nm, and 760 – 850 nm. We used orthorectified (level 3a) 25 X 25 km tile products in this study.

Four datasets were utilised in this study: The MoFLNRO vegetation resources inventory (VRI) disturbance polygons which were used to select the bitemporal image pairs ensuring they covered areas of recent disturbance (2) seven overlaying bitemporal Rapideye image pairs which contained several disturbance events occurring between acquisition times. (3) A set of 50 RapidEye images from across the Province were used to derive a set of tasseled cap coefficients, and (4) Earth Observation for the Sustainable Development of Forests Land Cover Classification
(EOSD LCC) was employed to mask non-vegetated areas from the 50 RapidEye images used to derive the tasseled cap coefficients. Each of these datasets is explained in more detail below.

### 2.2.1 Dataset 1: MoFLNRO VRI Disturbance Polygons

In BC, the VRI programme maps and catalogues geospatial information pertaining to BC’s forests. The VRI serves as a continuously updated archive and is implemented using photointerpretation, ground sampling, and satellite imagery. Aerial photos used in the VRI data are typically collected at a 1:10,000 scale prior to ground sampling. Updates of disturbance polygons (fire, harvest, and other events) are submitted to the MoFLNRO by licensees or through a variety of data collection sources (MoFLNRO, 2013) and can include both actual and planned harvests. For our analysis only contemporary VRI data was used to ensure the VRI disturbance polygons coincided with the RapidEye imagery dates. These polygons were indicated to have been gathered principally from aerial photographic interpretation, and ground sampling as well as Landsat satellite imagery and other GIS data provided by forest tenure holders. The VRI data also served as reference data to assess the accuracy of our estimated threshold between disturbed and unchanged forest.

### 2.2.2 Dataset 2: RapidEye Bitemporal Image Pairs

We located RapidEye tiles containing recent disturbances (i.e., since 2010) based on data from the MoFLNRO VRI polygons. The first image dataset consisted of 7 image pairs shown in Table 2.1. Of the 7 pairs selected, 4 contained only harvest activity, 2 contained only fires, and 1 contained both recent fires and harvest activity. Polygon files from the VRI disturbance database were used to delineate harvest and fire data across BC. In order to assess the capacity of RapidEye to detect these disturbance types, a stratification of disturbance events was undertaken by type. Image pairs were selected to occur within one month of their anniversary date to ensure
similar seasonal conditions. A total of 4484 ha of fire and 6114 ha of harvest was identified across the seven scenes.

2.2.3 Dataset 3: RapidEye TCT Images
A second set of 50 level 3a RapidEye images were acquired from five forested regions and used to derive a TCT. Images were selected to have <10% cloud cover (as indicated by the RapidEye cloud detection algorithm) and to have been recorded between June 21 and September 21, 2012. RapidEye digital numbers (DNs) were converted to Top of Atmosphere (TOA) reflectance as specified by the RapidEye product guide (RapidEye 2013).

<table>
<thead>
<tr>
<th>Tile ID</th>
<th>T1</th>
<th>T2</th>
<th>Indicated disturbance area (ha)</th>
<th>Total polygons (MoFLNRO)</th>
<th>Average size (ha)</th>
<th>Standard dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>harvest</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>962221</td>
<td>July 7, 2010</td>
<td>July 18, 2012</td>
<td>983</td>
<td>55</td>
<td>17.9</td>
<td>17.0</td>
</tr>
<tr>
<td>964123</td>
<td>July 23, 2010</td>
<td>July 24, 2012</td>
<td>1665</td>
<td>46</td>
<td>36.2</td>
<td>62.8</td>
</tr>
<tr>
<td>1062622</td>
<td>Sept. 9, 2011</td>
<td>Sept. 8, 2012</td>
<td>756</td>
<td>9</td>
<td>84.0</td>
<td>75.7</td>
</tr>
<tr>
<td>1063413</td>
<td>Aug. 11, 2011</td>
<td>Aug. 16, 2012</td>
<td>718</td>
<td>16</td>
<td>44.9</td>
<td>104.5</td>
</tr>
<tr>
<td>*1063414</td>
<td>July 24, 2010</td>
<td>Aug. 18, 2012</td>
<td>3058</td>
<td>53</td>
<td>57.7</td>
<td>72.4</td>
</tr>
<tr>
<td>fire</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>963622</td>
<td>July 13, 2010</td>
<td>July 23, 2012</td>
<td>572</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>1063908</td>
<td>July 17, 2010</td>
<td>Aug. 8, 2012</td>
<td>17966</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>*1063414</td>
<td>July 24, 2010</td>
<td>Aug. 18, 2012</td>
<td>3298</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

2.2.4 Dataset 4: EOSD LCC Derived Mask
The Earth Observation for the Sustainable Development of Forest Land Cover Classification (EOSD LCC) is a Landsat-derived classification scheme used to map Canada’s ecological...
regions (Wulder and Nelson 2003). Within EOSD data, six nested hierarchical levels exist to classify vegetated regions while five levels are used to classify non-vegetated regions (Wood et al. 2002). The EOSD LCC was used to mask areas of snow and ice, barren rock, and surface water prior to calculating a TCT from the 50 cloud free RapidEye images. Figure 2.1 describes the data processing flow used in this analysis.
2.2.5 Tasseled Cap Transformation

As TCT coefficients for RapidEye data were not readily available, we implement a PCA approach to derive an appropriate transformation. The PCA approach seeks uncorrelated linear
combinations of \( n \) bands by creating \( n \) uncorrelated principal components (e.g., Wold et al. 1987). The derived principal components are listed in decreasing order of explained variance. In general, correlations between band reflectance levels are accounted for in the same component, while uncorrelated data is distributed amongst other components (Crist and Cicone 1984). A set of eigenvalues are derived from the resulting covariance matrix, with each eigenvalue corresponding to a set of eigenvectors (TCT coefficients). By multiplying the derived eigenvalues by their respective band reflectance values results is a set of derived components (Gil Docampo et al. 2004). These components form the basis of the tasseled cap coefficients. The original TCT was conducted using a Gram-Schmidt Orthogonalization procedure, explained by Kauth and Thomas (1976). Generally, the first tasseled cap band is an agglomerative representation of overall image brightness, while the second band tends to emphasize overall ‘greenness’ of vegetation. Although RapidEye does not contain a SWIR band, a unique ‘red-edge’ band may be helpful in creating a third interpretable TCT index. Previous studies have demonstrated the red-edge region of the spectrum to be sensitive to chlorophyll concentration (Filella and Peñuelas 1994) and classification of vegetation type (Schuster et al., 2012). We used ENVI version 4.8 (Exelis Visual Information Solutions) to conduct PCA on covariance matrices to derive initial components. To achieve positive values for all pixels, a constant offset vector ‘\( r \)’ was then estimated to ensure TCT values occurred only in positive tasseled cap space. The constant offset vector was calculated from the minimum values across all 50 images.

### 2.2.6 Disturbance Index

The disturbance index (DI) proposed by Healey et al. (2005) takes advantage of the TCT for Landsat TM, whereby standardized greenness (Gr) and wetness (Wr) values are subtracted from standardized scene brightness (Br). The resulting index enhances differences between regions
that exhibit overall high values in all TCT indices from regions that contain only high brightness values, summarized as follows:

\[
Br = (B - B\mu)/B\sigma \\
Gr = (G - G\mu)/G\sigma \\
Wr = (W - W\mu)/W\sigma \\
DI = Br - (Gr + Wr)
\]

The derivation of DI bands allows for single band comparisons to be made between multitemporal imagery. To ensure transferability across images and dates, our analysis differs slightly from the original proposed by Healey et al. (2005). We standardized our images using z-scores calculated from all 50 images, whereby \( \mu \) and \( \sigma \) denote the mean and standard deviation calculated from all images. For our analysis, we subtracted \( T_1 \) from \( T_2 \) to create univariate difference images depicting probable change between image acquisitions. We anticipated that within each univariate difference image, negative values would indicate increased vegetation, positive values would indicate vegetation loss, and near-zero values would indicate no change.

2.2.7 Threshold Development

A simple threshold value was required to discriminate between disturbance and no-change cover types. As the VRI harvest polygons contain both actual and planned harvest schedule events, there were a number of polygons delineated for future harvest which had not yet been undertaken between the image dates. To detect and remove these events prior to any sampling, we used an interim threshold value of one standard deviation above the difference image’s mean pixel value. If the harvest polygon’s mean pixel value fell within one standard deviation of the difference image mean (indicative of no change) the polygon was designated as incomplete or erroneous.
and was removed from the sampling process. The remaining polygons are summarized in Table 2.2. Following the methods of Coops et al. (2006), we randomly extracted 1/3 of the remaining harvest polygons for threshold development, leaving 2/3 for accuracy assessment purposes.

<table>
<thead>
<tr>
<th>tile ID</th>
<th>confirmed harvest polygons</th>
<th>confirmed harvest area during interval (ha)</th>
<th>average confirmed polygon size (ha)</th>
<th>standard deviation (ha)</th>
<th>randomly selected polygons</th>
<th>randomly selected polygon area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>962221</td>
<td>41</td>
<td>737</td>
<td>17.98</td>
<td>16.30</td>
<td>14</td>
<td>272</td>
</tr>
<tr>
<td>964123</td>
<td>41</td>
<td>1105</td>
<td>26.95</td>
<td>36.16</td>
<td>14</td>
<td>295</td>
</tr>
<tr>
<td>1062622</td>
<td>9</td>
<td>701</td>
<td>77.89</td>
<td>72.51</td>
<td>3</td>
<td>255</td>
</tr>
<tr>
<td>1063413</td>
<td>11</td>
<td>365</td>
<td>33.18</td>
<td>40.75</td>
<td>4</td>
<td>202</td>
</tr>
<tr>
<td>1063414</td>
<td>40</td>
<td>1576</td>
<td>39.40</td>
<td>39.76</td>
<td>13</td>
<td>526</td>
</tr>
</tbody>
</table>

To derive robust threshold value of disturbance across all images and disturbance types, we randomly selected pixels within, and outside, the confirmed MoFLNRO disturbance polygons. Pixels were sampled at random at an average density of 10 pixels/ha within each disturbance event to a maximum of 10,000 pixels/polygon. An equal number of pixels were then selected at random from a 500 m buffer around the disturbance to represent no-change values (following Lee et al. 2013). Due to the limited number of fire events, fire polygons were divided into 1 ha cells, of which 1/3 were randomly selected and sampled at an average point density of 10 pixels/ha. An equal number of unburned pixels from a 500 m buffer around the entire burn area were sampled to represent no-change. A summary of burn scar areas is provided in Table 2.3.
Table 2.3 A Summary of burn scar and stratified sampling areas indicated to have occurred between image acquisition dates

<table>
<thead>
<tr>
<th>Tile ID</th>
<th>total fire area</th>
<th>stratified fire samples (1 ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>963622</td>
<td>572</td>
<td>162</td>
</tr>
<tr>
<td>1063908</td>
<td>17966</td>
<td>4947</td>
</tr>
<tr>
<td>1063414</td>
<td>3298</td>
<td>1009</td>
</tr>
</tbody>
</table>

A universal threshold value was then calculated as the difference between the mean disturbance and no-change pixel values from the seven difference images. The threshold was applied to the univariate difference images to create a set of seven binary threshold images (BTIs). Similar to Hill and Foody (1994), we then applied a 3 x 3 smoothing low pass filter to remove issues associated with single pixel misregistration.

2.2.8 Verification

Two approaches were used to estimate the accuracy of the disturbance detection method. The first approach utilised the VRI as reference data while the second approach relied on a random stratified sample of manually interpreted points. At each of the seven scenes a reference dataset was created using the VRI polygons. Each map comprised four classes depicting (1) disturbance agreement for VRI and BTIs, (2) no-change agreement between VRI data and BTIs, (3) change detected by BTI and not VRI, and (4) change indicated by VRI and not BTI. The EOSD dataset and RapidEye unusable data mask (UDMs) were also used to mask areas of cloud and non-vegetated cover, resulting in a total mapped area of 338,645 ha across the 7 tiles. Measures of pooled and individual accuracy were assessed for each map. The second verification process used a random stratified sample to select 100 random points from the disturbance class and 400 points from the no-change class. Each point was manually interpreted as “disturbed” or “no-change” by visually comparing the original T1 and T2 RapidEye images.
Olofsson et al. (2013a) described in detail the calculation of critical metrics which can be applied when assessing the accuracy of change detection maps; these were used as a basis for both accuracy assessments. The proportion of each class was estimated using an unbiased estimation matrix (Olofsson et al. 2013a). Confidence intervals depicting 95% confidence were also estimated using Olofsson et al. (2013b). Estimates of class accuracy using the VRI reference data relied on a random sample of 10,000 pixels/tile, while manually interpreted approach relied on a smaller sample of 500 pixels.

2.3 Results

The results of the PCA transformation on the 50 near-cloud free TOA RapidEye images are shown in Table 2.4 indicating the individual band loadings by component.

<table>
<thead>
<tr>
<th>component band</th>
<th>blue</th>
<th>green</th>
<th>red</th>
<th>red edge</th>
<th>NIR</th>
<th>Variance Explained (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.293</td>
<td>-0.354</td>
<td>-0.372</td>
<td>-0.440</td>
<td>-0.676</td>
<td>75.66</td>
</tr>
<tr>
<td>2</td>
<td>-0.406</td>
<td>-0.367</td>
<td>-0.446</td>
<td>-0.128</td>
<td>0.697</td>
<td>23.01</td>
</tr>
<tr>
<td>3</td>
<td>0.572</td>
<td>0.402</td>
<td>-0.494</td>
<td>-0.498</td>
<td>0.138</td>
<td>1.04</td>
</tr>
<tr>
<td>4</td>
<td>0.131</td>
<td>-0.309</td>
<td>0.632</td>
<td>-0.671</td>
<td>0.195</td>
<td>0.20</td>
</tr>
<tr>
<td>5</td>
<td>0.636</td>
<td>-0.695</td>
<td>-0.141</td>
<td>0.302</td>
<td>-0.030</td>
<td>0.09</td>
</tr>
</tbody>
</table>

As anticipated, the first three PCs explained over 99% of the variance within the image data. Figure 2.2 provides a visual comparison of these first three components. As expected, the first component (TCT\textsubscript{1}) represents overall scene brightness with recently harvested areas expressed as lighter grey and mature forest stands expressed as darker grey. The second component (TCT\textsubscript{2}) appears to be sensitive to vegetation cover, with darker values representing recently cut
vegetation and lighter values representing recovering forest and young vegetation. Despite the third component (TCT₃) accounting for less than 1% of total image variability, areas of recent harvest are clearly distinguished by dark pixels and as a result this component remained in the analysis. To achieve positive space for all pixel values and complete the transformation, TCT₁ values were multiplied by -1 and constant offset vectors were estimated to be 0, 0.93, and 0.74 for TCT₁, TCT₂, and TCT₃, respectively.

Figure 2.2 Visual comparisons of three derived tasseled cap indices for an area containing various stages of forest succession, approximately 55 km southeast of Vanderhoof, BC, RE Tile ID 1063813. From left to right: TCT₁, TCT₂, TCT₃

Two-dimensional scatter plots depicting the first 3 TCTs are shown in Figure 2.3. Several common land cover types are outlined depicting their relative location within the tasseled cap space.
Figure 2.3 2D scatter plots depicting density slices of RapidEye tile 1063813, an area approximately 55 km southeast of Vanderhoof, BC.

Figure 2.4 provides visual comparison of TOA reflectance values for blue, green, and red bands compared to TCT₁, TCT₂, and TCT₃. The TCT bands show good differentiation of between various stages of forest recovery when compared to the RGB image.

Figure 2.4 a comparison of TOA RapidEye (RGB) image and Tasselled Cap image, approximately 55 km southeast of Vanderhoof, BC. Recently cleared areas appear red, recovering regions are orange, stable areas are in blue. Image size is approximately 4 X 4 km. TCT₁, T TCT₂, TCT₃ are displayed using red, green, and blue colour guns respectively.
Across all 7 images and both disturbance types, the mean disturbed pixel value was $\mu = 1.62$ ($\sigma = 1.62$) while the unchanged pixel value was $\mu = -0.03$ ($\sigma = 0.79$). A t-test between disturbed and undisturbed classes revealed that differences were statistically significant ($p<0.05$). For individual disturbances, the pixel values differed with the mean harvest pixels ($\mu = 2.99$) differing significantly from fire ($\mu = 0.64$) ($p<0.05$) as shown in Figures 2.5 and 2.6. A universal threshold value across all scenes was calculated as 0.79, above which all pixels were classified as changed.

Figure 2.5 A comparison of random stratified disturbance index values for burned and un-burned areas (sampled at a density of 10pts/ha). Unburned areas were sampled at random from a 500 m buffer around the indicated disturbance ('Fire' = from within burned area, ‘NC’ = from within no-change area).
Figure 2.6 A comparison of random stratified disturbance index values for harvested and non-harvested areas (sampled at a density of 10pts/ha). Non-harvested areas were sampled at random from a 500 m buffer around the indicated disturbance (‘Cut’ = from within harvested area, ‘NC’ = from within no-change area).

Figure 7 shows the application of the threshold for recently disturbed features using this 0.79 threshold. Areas outlined in red show MoFLNRO harvest polygons. As indicated by Figure 2.7, several MoFLNRO polygons do not align with the extracted disturbance layer.
Table 2.5 reports the accuracy of the disturbance classification using the methods of Olofsson et al. (2013a) using the VRI polygons as reference data. The overall accuracy across the landscape is high, ranging between 89% and 96%. Overall, harvest was more successfully detected than fire. The large number of unchanged pixels, however, heavily weights the overall accuracy of the delineation. This weighting of non-disturbed areas results in very high user’s and producer’s accuracy for un-disturbed areas and lower accuracies for the disturbed areas; as a result it is best to compare individual user’s and producer’s accuracies.

Classification accuracies using the VRI polygons as reference data resulted in varying accuracies amongst tiles (Table 2.5). For example tile 1062622, near Kamloops, BC reported respective user’s and producer’s accuracies of 8.71 ± 1.63 and 65.83 ± 13.94. Tile 964123, near Burns Lake, BC demonstrated much better alignment with the VRI polygons and overall higher classification accuracies. Tile 964123 reported user’s and producer’s accuracies of 51.83 ± 5.65 and 56.58 ± 5.37, respectively. Classification results from tile 964123 aligned well with the VRI polygons, with 34 of 46 harvest polygons overlaying consistently. Other individual tile classification results, such as tile 962221 on northern Vancouver Island, did not perform as well and contained substantial mismatches between the VRI disturbance layers and the detected disturbances.
Table 2.5 Disturbance accuracies for individual tiles used in disturbance classification, D = Disturbance, N = No Change classes. Columns D and N represent sample proportions of map class (n = 10,000 samples/tile)

<table>
<thead>
<tr>
<th>Tile ID (map)</th>
<th>D (%)</th>
<th>N (%)</th>
<th>User's Acc. (%)</th>
<th>Producer's Acc. (%)</th>
<th>Overall Acc. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>962221</td>
<td>0.66</td>
<td>2.02</td>
<td>24.56 ± 3.97</td>
<td>58.88 ± 8.07</td>
<td>97.52 ± 0.17</td>
</tr>
<tr>
<td></td>
<td>0.46</td>
<td>96.87</td>
<td>99.53 ± 0.14</td>
<td>97.96 ± 2.24</td>
<td></td>
</tr>
<tr>
<td>963622</td>
<td>0.58</td>
<td>2.09</td>
<td>21.86 ± 3.77</td>
<td>57.09 ± 8.44</td>
<td>97.47 ± 0.17</td>
</tr>
<tr>
<td></td>
<td>0.44</td>
<td>96.89</td>
<td>99.55 ± 0.13</td>
<td>97.89 ± 2.14</td>
<td></td>
</tr>
<tr>
<td>964123</td>
<td>1.39</td>
<td>1.29</td>
<td>51.83 ± 5.65</td>
<td>56.58 ± 5.37</td>
<td>97.65 ± 0.25</td>
</tr>
<tr>
<td></td>
<td>1.06</td>
<td>96.26</td>
<td>98.91 ± 0.21</td>
<td>98.68 ± 2.65</td>
<td></td>
</tr>
<tr>
<td>1062622</td>
<td>0.23</td>
<td>2.44</td>
<td>8.71 ± 1.63</td>
<td>65.83 ± 13.94</td>
<td>97.44 ± 0.08</td>
</tr>
<tr>
<td></td>
<td>0.12</td>
<td>97.20</td>
<td>99.88 ± 0.07</td>
<td>97.55 ± 1.45</td>
<td></td>
</tr>
<tr>
<td>1063413</td>
<td>0.25</td>
<td>2.42</td>
<td>9.40 ± 1.98</td>
<td>33.03 ± 7.78</td>
<td>97.07 ± 0.15</td>
</tr>
<tr>
<td></td>
<td>0.51</td>
<td>96.82</td>
<td>99.48 ± 0.15</td>
<td>97.56 ± 1.5</td>
<td></td>
</tr>
<tr>
<td>1063414</td>
<td>1.94</td>
<td>0.73</td>
<td>72.57 ± 3.33</td>
<td>28.36 ± 2.02</td>
<td>94.36 ± 0.44</td>
</tr>
<tr>
<td></td>
<td>4.90</td>
<td>92.42</td>
<td>94.96 ± 0.44</td>
<td>99.21 ± 2.49</td>
<td></td>
</tr>
<tr>
<td>1063908</td>
<td>2.48</td>
<td>0.19</td>
<td>92.85 ± 1.28</td>
<td>13.32 ± 0.57</td>
<td>83.65 ± 0.77</td>
</tr>
<tr>
<td></td>
<td>16.16</td>
<td>81.17</td>
<td>83.40 ± 0.79</td>
<td>99.77 ± 1.66</td>
<td></td>
</tr>
<tr>
<td>Total Harvest</td>
<td>0.91</td>
<td>2.93</td>
<td>23.75 ± 1.70</td>
<td>57.24 ± 3.44</td>
<td>96.38 ± 0.10</td>
</tr>
<tr>
<td></td>
<td>0.68</td>
<td>95.47</td>
<td>99.28 ± 0.08</td>
<td>97.02 ± 3.16</td>
<td></td>
</tr>
<tr>
<td>Total Fire</td>
<td>11.54</td>
<td>3.53</td>
<td>76.58 ± 1.80</td>
<td>62.83 ± 1.28</td>
<td>89.64 ± 0.43</td>
</tr>
<tr>
<td></td>
<td>6.83</td>
<td>78.11</td>
<td>91.96 ± 0.39</td>
<td>95.67 ± 14.65</td>
<td></td>
</tr>
<tr>
<td>Grand Total</td>
<td>3.19</td>
<td>4.43</td>
<td>41.87 ± 1.31</td>
<td>52.22 ± 1.32</td>
<td>92.64 ± 0.15</td>
</tr>
<tr>
<td></td>
<td>2.92</td>
<td>89.46</td>
<td>96.83 ± 0.13</td>
<td>95.27 ± 0.10</td>
<td></td>
</tr>
</tbody>
</table>

The manually verified classification reported much higher measures of user’s and producer’s accuracies (Table 2.6). User’s and producer’s accuracies were 75 ± 9% and 87.75 ± 10.56% for
the disturbance class and 99 ± 0.98% and 96.64 ± 7.81% for the no-change class, respectively. The Overall classification accuracy was 96.91 ± 1.16%. During the manual classification process it was noted that 11 of the 25 pixels that were misclassified as disturbance occurred within regions of unmasked cloud or snow cover. The misclassification snow and cloud suggested that classification accuracy could be increased by implementing a more effective cloud and snow mask. Removing the 11 misclassified cloud and snow pixels resulted in disturbance classification accuracies of 84.27 ± 7.61%, 88.95 ± 9.64%, 97.72 ± 1.11% for user’s, producer’s and overall accuracies, respectively.

Table 2.6 Manually verified accuracy for overall disturbance classification, D = Disturbance, N = No Change classes. Columns D and N represent sample proportions of map class (n = 100 samples/tile)

<table>
<thead>
<tr>
<th>Tile ID (map)</th>
<th>DD (%)</th>
<th>NC (%)</th>
<th>User's Acc. (%)</th>
<th>Producer's Acc. (%)</th>
<th>Overall Acc. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Area</td>
<td>D</td>
<td>0.07</td>
<td>0.02</td>
<td>75 ± 8.53</td>
<td>87.75 ± 10.56</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>0.01</td>
<td>0.90</td>
<td>99 ± 0.98</td>
<td>97.64 ± 7.81</td>
</tr>
</tbody>
</table>

2.4 Discussion

RapidEye and similar ongoing and proposed constellations provide opportunities for combining fine spatial resolution with frequent monitoring. Continuous coverage provided by constellation platforms offers improved data availability over single sensor platforms. Furthermore, we found that cloud free imagery was readily available, even for coastal BC, where cloud cover is extremely high. Our simple disturbance index, derived from selective PCA on RapidEye imagery proved useful in detecting disturbance. Further research should be carried out to assess the relationship between the RapidEye TCT values and the spectral characteristics of real surface features allowing for more detailed interpretation of indices.
Although conventional principal components literature suggests that only the first two components from our analysis should be retained (Jackson 1993), a visual assessment of the third derived TCT band (Figure 2.2) clearly distinguishes between recently cleared areas and standing vegetation, providing further support for the inclusion of the third TCT component. Horne (2003) chose to interpret all 4 components derived from 4 IKONOS bands, despite components 3 and 4 explaining only 1.54% and 0.17% of the image variance, respectively. Similar to Horne’s (2003) transformation for IKONOS, our third component can be generalized as the blue and green bands minus red and red-edge bands, and appears useful in the delineation of disturbed areas.

Overall, the locations of data structures within TCT space are consistent with descriptions of TCT from other studies (e.g., Crist and Cicone 2004; Horne, 2003; Yarbrough et al., 2005). Although RapidEye contains a unique red-edge band (690-730 nm), the relative weighting of the red-edge did not provide a distinctive response for any components. A visual assessment of 2D scatter plots (Figure 2.3) shows many similarities to Crist and Cicone’s (1984) original description of Landsat TM TCT.

2.4.1 Accuracy Interpretation

It is crucial to use appropriate accuracy estimation metrics for any land cover classification exercise. Best practices for assessing the accuracy of the change should calculate confidence intervals surrounding each respective class (Strahler et al. 2006). Furthermore, commonly used statistical measures, such as Cohen’s Kappa statistic do not provide adequate description of classification accuracy. Cohen’s Kappa is simply a probabilistic measure of random agreement between two maps and does not account for estimates of uncertainty (Stehman 1997). The unbiased estimator approach described by Olofsson et al. (2013a) meets “best practice”
requirements for the assessment and classification of land cover classes and was therefore employed in this study.

The threshold approach proved useful in the identification of structural forest disturbances. Unbiased estimates of producer’s accuracy revealed that cumulative producer’s accuracy was greater than cumulative user’s accuracy for all disturbed areas (42 ± 1.3% and 52 ± 1.3%, respectively) using the VRI as reference data. This result implies that approximately half of the disturbance areas provided in VRI data did not align with areas classified using the threshold method, likely due to a variety of sources including error within VRI (Olofsson et al. 2013a).

Large discrepancies between detected disturbance and VRI reference data resulted in a low estimate of cumulative user’s accuracy. The overall 23.8 ± 1.8% estimate of user’s accuracy for harvest can be interpreted as “23.8 ± 1.8% of the area identified as harvest matched the VRI reference data”. The low user’s accuracy estimate should not discredit the utility of the disturbance index, which was supported by the manually verified dataset. Low estimates of user’s accuracy can be caused by (1) overestimating of the extent of disturbances, or (2) errors within reference data. Errors within reference data are common and likely contributed to the low accuracy assessment results (Congalton and Green, 1993; Foody, 2010). In general terms, the user’s accuracy is the number of correctly classified units divided by the total number of units mapped as that particular class, suggesting there may have been many disturbances that were not included in the VRI reference data. In several instances, the VRI data depicted obvious discrepancies between the location of disturbances and observed changes in the disturbance index, both of which can be seen in Figure 2.7.
The estimated producer’s accuracy from the detection disturbance by harvest was much higher with an estimated $57.2 \pm 3.4\%$ of the harvest data classified as disturbance. The producer’s accuracy is a measure of omission error and is not related to the overestimation of disturbance. Failing to detect disturbances will produce a low estimate of producer’s accuracy. Similarly, a low producer’s accuracy may be obtained if disturbances did not actually occur between image acquisition times. Producer’s accuracy was likely affected by the reference data containing disturbances that had not occurred between image acquisition times, also apparent in Figure 2.7.

Interpretation of the differences between the user’s and producer’s accuracies provides an indication of the accuracy of the VRI data itself. For example, high producer’s accuracies are indicative of VRI disturbances aligning with detected disturbance layers. This producer’s accuracy is also consistently higher across all harvest sites, indicating that if RapidEye detected a disturbance, it was very often included within the VRI. Lower user’s accuracies potentially indicate that there are disturbances that are not included in the VRI. Alternatively, a low user’s accuracy could also imply a hypersensitive disturbance threshold, resulting in a subsequent overestimation of disturbance. In reality, estimates of classification error derived from confusion matrix data will likely contain both types of error included in the accuracy assessment. However, the stratified approach provides a useful way to estimate the level of accuracy to which we can assess the degree of disturbance (Olofsson et al. 2013a).

The manually interpreted reference data supports the contention that many of the VRI polygons did not serve as adequate reference data, as much higher accuracies reported by the 500 manually interpreted pixels.
2.4.2 Assessment of Burned Areas
Classifying the full extent of burned areas presented several challenges to the threshold-based approach. Although the general extent of the detected burned area appears to have aligned well with the VRI data, the inherent patchy nature of forest fires appears to have caused several discrepancies between reference and mapped areas (Rowe and Scotter 1973; Kachmar and Arturo Sánchez-Azofeifa 2006). Reference polygons represented a simplification of fire extent and did not incorporate patchiness or residual unburned areas within the fire bounds. It was also apparent that many regions within burned areas exhibited a negative disturbance index, indicative of increased vegetation. This was likely due, in part, to the large degree of heterogeneity within burned areas. As a result, the single universal threshold produced maps depicting extremely patchy burn scars.

2.4.3 Impact of Atmospheric Distortion
The disturbance index threshold appears to overestimate disturbed pixels in the presence of smoke or haze. Clouds present a variety of challenges in land cover monitoring studies (Sano et al. 2007). These challenges appeared to have been exacerbated by RapidEye’s lack of a thermal band, which is often used to detect cloud cover in many screening algorithms (Hollingsworth et al. 1996; Choi and Bindschadler 2004; Goodwin et al. 2013). Although RapidEye does provide an unusable data mask (UDM) targeted at detecting clouds in imagery, smaller clouds, haze, smoke, and cloud edges are often missed. Cloud shadow also provided an additional source of error evident in a number of images. Cloud shadows in the T2 image were often misclassified as disturbance as overall reflectance values were lower in the second image. Presence of haze can also be clearly seen in images 1062622, and to a lesser extent in 1063413, and in many cases this was classified as disturbance. Clouds present challenges to all optical remote sensing exercises. While cloud contamination may be inevitable given seasonal constraints of image acquisition,
the constellation format of RapidEye allows for greater image selection over single-sensor platforms.

2.4.4 Threshold Selection

Our universal binary threshold provided a simple, robust method for differentiating between two cover classes, and may not result in optimal extraction of disturbance features across vegetation types and across different seasons. A more accurate disturbance classification could be produced depending on the context of disturbance and the area of interest. Once difference images are produced a variety of more complex methods can be used to differentiate threshold values using the image histogram. Furthermore, the application of a specific thresholding algorithm could also be used to potentially estimate an optimal change threshold. In an assessment by Patra et al. (2011), six image threshold algorithms were evaluated based on their ability to differentiate between changed and unchanged regions. After deriving a difference image, any single band thresholding algorithm could be applied to extract change classes from within imagery.

Our universal threshold likely overestimated the area of stand replacing forest disturbances. This could be attributed, in part, to pixels sampled from large fire polygons which encompassed both severely and less severely burnt vegetation. This overestimation of disturbance was also notable in pixels where there was some evidence of atmospheric haze and unmasked clouds, apparent for tiles 1062622 and 962221. Figure 2.8 demonstrates how changing the threshold value can affect the classification accuracies. In this particular image, increasing the disturbance index threshold appears to increase both user’s and producer’s accuracies for the detection of disturbance, suggesting that our estimated threshold may have been overly sensitive to inherent spectral differences between the bitemporal images.
2.4.5 Future Applications

The readily available imagery and fine spatial resolution of RapidEye could allow for the exploration of many additional applications. In Canada, forest inventories typically combine spatial data on forest attributes such as stand age, species composition, as well as various structural and health traits (McRoberts and Tomppo 2007). Canadian forest inventory monitoring approaches combine metrics derived from ground plot data, aerial photography, and satellite imagery to estimate forest cover and change at provincial and national scales (Pitt and Pineau 2009). These inventories can take years to produce (Leckie and Gillis 1995); thus, current information on forest stands is often lacking. In addition, newer inventories are often conducted using inconsistent measurement techniques as novel technologies are adopted (Gillis 2001). Comprehensive inventories, such as those produced by Light Detection and Ranging (LiDAR), provide opportunities for estimating detailed structural stand attributes. However, wall-to-wall
LiDAR coverage is not yet operationally feasible (Woods et al. 2011). In order to routinely update these inventories, maps are often updated every one to five years using disturbance information.

Other nations routinely use satellite imagery to detect disturbance on the forested landbase. The Brazilian PRODES programme is a successful forest monitoring project aimed at tracking annual deforestation throughout the Amazon basin (INPE, 2013). The PRODES dataset is updated using 117 Landsat Thematic Mapper (TM) scenes to derive a comprehensive spatial product depicting deforestation. The annual product provides a snapshot of deforestation throughout the Amazon, yet it lacks frequent temporal updates required to address illegal harvest activities as they occur (Shimabukuro et al., 2006). A complementary project, the Deforestation Detection in Real Time (DETER), is focused on the enforcement of regulations regarding logging activity using MODIS. The DETER programme is capable of achieving bi-weekly updates, however the spatial resolution is limited to a minimum mapping unit of 25 ha (Assunção et al. 2013). Both the Canadian and Brazilian examples highlight the need for more frequent and finer scale monitoring to meet national forest monitoring needs. The spatial and temporal resolutions provided by RapidEye would complement both forest inventory programmes and improve their ability to effectively monitor forest cover at scales relevant to the countries’ respective needs.

In addition to forest inventory applications, monitoring disturbance using RapidEye could provide substantial improvements for monitoring resource extraction activities. For example, concerns over the integrity of pipelines in BC and abroad could potentially be addressed through frequent satellite monitoring. Pipeline corridors often occur in remote regions and are affected by geophysical changes to the landscape. Forest disturbance events can affect slope stability and should be considered within a pipeline monitoring context (Pradan et al. 2008). To ensure
pipeline safety, remote sensing of pipeline corridors could become an integral component of the monitoring requirements used by the oil and gas industry (Hausamann et al. 2005).

Assessing habitat fragmentation metrics is another potential application that could be exploited using the RapidEye disturbance index approach. Land cover maps provide vital information on a suite of ecological characteristics used to quantify important variables associated with habitat and biodiversity (Boykin et al., 2013). Assessing trends, changes, and patterns in vegetation cover are common goals shared amongst global and national monitoring administrations (Ståhl et al. 2011). The ability of the RapidEye disturbance index to detect and quantify spatial patterns relevant to habitat fragmentation scales presents opportunities for fine scale habitat assessment.

The following suggestions are provided to improve the quality and accuracy of change detection using imagery from the RapidEye constellation:

- Our approach to change detection applied a basic form of radiometric correction (conversion to TOA reflectance). More rigorous radiometric corrections could be applied prior to implementing our change detection technique
- Threshold optimization could potentially serve as a method of feature extraction, improving our ability to extract disturbed areas from satellite imagery (see Patra et al. 2011)
- More robust snow, cloud, and cloud shadow detection techniques should be employed

2.5 Conclusion

Our British Columbian example highlighted the ability of RapidEye to detect disturbances over large areas, showing the potential for an automated threshold index type approach to be applied over the entire province. Our findings suggest that RapidEye could be employed to monitor
change at a regional- or national-level and could aid in wall-to-wall forest monitoring programmes. The use of the RapidEye constellation to achieve continuous monitoring on a yearly basis, or near real-time updates of specific areas, could be beneficial to administrative or government commitments to assessing forest cover. In addition, RapidEye’s ability to provide imagery at much finer spatial and temporal resolutions compared to conventional single-sensor platforms makes it an attractive alternative to monitoring forest change over other conventional approaches. Deriving a simple disturbance index for RapidEye imagery successfully delineated disturbances throughout the 7 image pairs tested. In many instances the VRI disturbance layer did not align with obvious disturbances detected by RapidEye, and this likely deflated our estimates of accuracy when using the VRI as reference data. Our results suggest that these methods could be implemented in an automated or semi-automated fashion to detect disturbance covering large areas.
3 DETECTING FOREST DAMAGE AFTER A LOW-SEVERITY FIRE USING REMOTE SENSING AT MULTIPLE SCALES

3.1 Introduction

Fires play an important role in determining the structure and composition of forest ecosystems (Franklin et al. 2002, Turner 2010). The legacy of fire on landscapes can have major impacts on the composition and ecological function of forests in western North America (Palmer et al. 1997). Fire suppression during the 20th century has resulted reduced forest heterogeneity, potential reductions in biodiversity, and the accumulation of fuels, particularly in dry forest types (Schoennagel et al. 2004, Adams 2013). The lack of surface fires in some dry forests has led to the fuel accumulations woody surface fuels and has increased chance of severe wildland and interface fires (Miller et al. 2009). Yet management protocols regarding the normative state of fire on the landscape remains a contentious issue, even amongst researchers (Fule et al. 2013, Odion et al. 2013).

Fire is a dominant agent of forest disturbance in many North American forests (Bond-Lamberty et al. 2007, Perry et al. 2011). The effects of fire may exhibit a range of spatial and temporal changes to forested ecosystems (Landres et al. 1999). Post fire effects may be immediate, through the direct consumption of living and dead vegetation (Simard et al. 2001) or as lasting legacies, such as changes in forest structure (Turner et al. 1994). Fire can also change the geophysical and geochemical properties of soil, including the soil’s availability to store nutrients and retain water (Certini 2005). In western North America many forest types have evolved to

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2 A version of this chapter has been submitted for publication. Arnett, J.T.T.R., Coops, N.C. Daniels, L.D., Gergel, S.E., Falls R.W. 2014. Detecting forest damage after a low-severity fire using remote sensing at multiple scales.
rely on fires as an important process for maintaining the ecological integrity of the system (Habeck and Mutch 1973, Allen et al. 2002).

Emissions from wildfires contribute substantially to global carbon emissions (Schimel and Baker 2002), thus global, national, and regional carbon accounting frameworks are tuned to address concerns over emissions from wildfires (Hurteau et al. 2008). Currently research is underway to monitor carbon emissions from fires in both the United States and Canada (Masek et al. 2013). The Canadian National Carbon Forest Monitoring programme (NCFM) as well as the American Monitoring Trends in Burn Severity project (MTBS) are both mandated to estimate emissions produced by forest fires at a national scale (Eidenshink et al. 2007).

Wildfires present a paradox with respect to sustainable forest stewardship and carbon emission targets. Prescribed burning of forest fuels is often seen as a means of managing ecosystems by reducing fuel loading and increasing forest resistance to severe fires; however, these practices also contribute considerably to atmospheric carbon through fuel combustion and smoke production (Weidinmyer et al. 2010, Pan et al. 2011). Improved monitoring of fires will allow for a better understanding of the trade-offs between ecological and climatological objectives. Remote sensing provides the only feasible solution to operationalize both local and national monitoring of fires (Kerr and Ostrovsky 2003).

Conventional assessment of fire metrics often relies on the collection of field data after the fire has occurred, these data may include estimates of canopy consumption, surface fuels consumption (Key 2005), plant mortality (Larson and Franklin 2005), and changes to soil properties (Ice et al. 2004). Since fire is arguably unpredictable across the landscape, pre-fire conditions are often inferred or estimated after the fire has occurred (Lentile et al. 2006). Several
standardized surveys have been adapted to assess the severity and intensity of fire on forested communities. The composite burn index (CBI) has been adopted as a means of assessing fire severity due to the indices ability of correlate with remotely sensed imagery and combines measures of fire severity from below and above the canopy (Kasischke 2008)

Using optical remote sensing technologies to assess fire damage relies on the attribution of damage to vegetation to spectral changes recorded by the sensor. Mapping the extent and impacts of fire using remote sensing can provide information on the presence/absence of fires or discrete severity classes along a gradient of spectral changes caused by the loss or damage of vegetation (Lentile et al. 2006). Fire severity classes derived from remote sensing are often somewhat arbitrary and do not necessarily reflect empirical changes in forest cover or consumed biomass (Lentile et al. 2006). Furthermore, the mapping of specific burn attributes using remote sensing has been most frequently applied to large, severe and stand replacing disturbances (Epting et al. 2005). As fires encompass a vast range of severity, intensity, and scalar gradients across a range of ecosystems it is necessary to develop fine scale methods to accurately monitor post-fire effects on the vegetation (Eidenshink et al 2007). New remote sensing platforms offering higher spatial resolution, more frequent image acquisition times, and specific band configurations offer many opportunities to study the effects and impacts of fire on vegetation (Arroyo et al. 2008).

The Landsat series of satellites has been successfully used to map and monitor large fires (Masek et al. 2013). However, finer spatial detail and more frequent acquisition of imagery may be more desirable to a variety of disciplines including ecology, risk assessment, and carbon accounting (Whitman et al. 2013, de Groot et al. 2007).
The RapidEye satellite constellation includes 5 identical satellite sensors, which acquire high-spatial resolution (5 X 5 m) imagery at daily intervals. In addition to the sensors’ spatial resolution and temporal frequency, RapidEye has a unique red-edge band, as well as bands strategically placed in the visible and near-infrared (NIR) portions of the electromagnetic spectrum, making it an ideal sensor for monitoring vegetation (Bindel et al. 2011). Conventional Earth observing satellites, such as Landsat, provide imagery at a coarser spatial resolution but may offer several advantages over RapidEye, including wider swath coverage, more bands including in the shortwave infrared region of the spectrum, a lengthy historical data archive, as well as radiometrically-corrected imagery provided at no cost. Furthermore the longstanding availability of Landsat data has allowed for the much research on the sensor’s abilities to detect and monitor change on the Earth’s surface (Wulder et al. 2008).

A variety of change detection techniques can be used to identify fire and other disturbances using satellite imagery. Tracking of ground surface change using satellite imagery is generally conducted by the use of multitemporal, co-registered imagery (Coppin et al. 2004). Differences are then mapped by observing relatively large magnitude changes in surface reflectance between individual pixels (Coppin et al. 2004). The simplest change detection technique involves the subtraction of pixel values from one image to another co-registered image (Singh et al. 1989). Mapping change, however, is generally not undertaken on individual spectral bands. Vegetation indices, or band ratios, are usually derived prior to any image differencing (Singh et al. 1989; Lu et al. 2004). Indices derived from algebraic operations using band reflectance values are preferable because (i) indices are able to normalize the magnitude of change between images that may exhibit slightly different spectral levels (Huete et al. 2002) and (ii) because vegetation indices have been correlated with specific structural, physiological, and chemical responses of
vegetation due to stress or disturbance (Gao, 1996; Carlson and Ripley, 1997; Sims and Gamon 2003). Most vegetation indices are used to create a single grey-scale univariate difference image however some indices, such as the Normalized Burn Ratio (NBR), can rely on a single image to detect fire (Epting et al. 2005). To map the extent of subtle disturbances, such as non-stand-replacing fires it is necessary to incorporate detailed spatial data, beyond the 30 X 30 m resolution provided by Landsat.

In this paper we explore the potential of a RapidEye image time series to detect changes in vegetation following a low-intensity prescribed fire that aimed to reduce surface fuels in a dry forest in western Canada. Spatial semi-variance statistics were calculated to compare the level of variability between imagery from the RapidEye and Landsat sensors. Several commonly used spectral vegetation indices were then used to assess spectral differences before and after fire. These differences were then correlated with aggregate measures of damage to individual trees.

Estimating burn severity using optical remote sensing tends to emphasize changes associated with the forest canopy (Falkowski et al. 2004, Key and Benson 2006). Estimates of consumed sub-canopy fuels are largely unavailable when using optical remote sensing (Miller et al. 2003); however, these fuels may contribute substantially to forest biomass stocks. It is therefore necessary to include sub-canopy measures of burn severity along with overall estimates of canopy scorch to calculate consumed biomass due to fires. To account for damage to the sub-canopy, metrics of individual tree damage were combined into a Simple Burn Index (SBI), which was then compared to remotely sensed imagery.

Finally, we derived and mapped a set of burn severity classes and estimated consumption of woody surface fuels and biomass throughout the study area. In this study we hypothesize that
estimates of burn impacts derived from RapidEye satellite imagery will be able to resolve stand
damage at the individual tree level. It is expected that finer-scale disturbance attributes derived
from RapidEye will be able to provide a more detailed assessment of the burn damage than
conventional analysis of Landsat-imagery.

3.2 Site Description

This study was conducted in the West Vaseux Lake unit of the Vaseux-Bighorn National
Wildlife Area (VBNWA), located in the Southern Okanagan Region of British Columbia,
Canada (Figure 3.1). The VBNW presents an ideal opportunity to assess the capacity of remote
sensing due to the availability of pre- and post-fire forest and fuels data, an attribute often
lacking in disturbance remote sensing studies. The forest includes a mix of Douglas-fir
(Pseudotsuga menziesii) and Ponderosa pine (Pinus ponderosa), with an approximate density of
250 trees ha\(^{-1}\). The VBNWA is a protected area managed by the Canadian Wildlife Service to
sustain habitat and populations of more than 30 threatened and endangered species (Cooper et al.
2011). Conservation interest for the area has led to the reintroduction of fire as an ecological
process that has largely been suppressed since European settlement. In March 2013, the
Canadian Wildlife Service (CWS), in collaboration with the BC Wildfire Management Branch,
conducted a prescribed fire in the VBNWA to re-introduce fire, restore critical wildlife habitat,
mitigate fuel build-up to decrease the risk of a severe wildfire and increase ecosystem resilience
to climate change (Mottishaw 2013).
3.3 Methods

3.3.1 Field Data
Trees (n =116, diameter at breast height (DBH) > 5cm) were sampled at 15-m intervals along 4 established transects using a point-center-quarter method (Cottam and Curtis 1953) and measured before and after the burn. Indicators of burn damage included (1) burn circumference; a measure of the scorched area around the base of the tree, (2) char height; the height of charring up the tree divided by the extrapolated tree height (derived from DBH), and (3) estimated crown scorch expressed as a percent of the total unburned crown. Summaries of the fire damage estimates are provided in Figure 3.2.
Woody surface fuels (diameter ≥ 2.6cm) were sampled along each transect using the line intercept method (van Wagner 1968). Before the burn, the locations of each piece of wood along transects were recorded, species was determined and diameter measured with calipers. Steel wire was tied at the intersection point so that the wood could be re-measured after the burn. Species-specific wood density (Gonzalez 1990) was used to calculate the biomass of each piece of wood before and after the burn.

Measures of burn circumference, char height, and crown scorch were combined to derive a simple burn index (SBI). The SBI provided a meaningful estimate of burn severity for individual trees. Based on the relative stand closure we estimated weightings for the sub-canopy attributes to contribute to 20% (evenly split between the burn circumference and char height measures) and canopy reflectance to contribute to 80% of the SBI. Figure 3.2 provides a visual depiction of the variability of burn attributes recorded for individual trees in this study.

![Graph showing variability of burn attributes](image)

Figure 3.2: Field data for individual tree damage estimates for the 115 trees sampled. The combined burn percentage ranges from 0-300%, as three variables were summed.
3.3.2 Satellite Imagery

Two satellite image pairs were used in the analysis. Image pairs from before and after the fire were acquired from both RapidEye and Landsat (TM+ and OLI) sensors. A summary of the images used is provided in Table 3.1. Image pairs were selected to be cloud free and within 20 days of each other’s respective anniversary date to mitigate any seasonal radiometric differences.

<table>
<thead>
<tr>
<th>Image</th>
<th>Date Recorded</th>
<th>Specific Sensor</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RapidEye T1</td>
<td>June 11, 2012</td>
<td>RapidEye 5</td>
<td>5</td>
</tr>
<tr>
<td>RapidEye T2</td>
<td>June 30, 2013</td>
<td>RapidEye 3</td>
<td>5</td>
</tr>
<tr>
<td>Landsat T2</td>
<td>June 21, 2011</td>
<td>Landsat 5 (TM)</td>
<td>30</td>
</tr>
<tr>
<td>Landsat T2</td>
<td>June 10, 2013</td>
<td>Landsat 8 (OLI)</td>
<td>30</td>
</tr>
</tbody>
</table>

3.3.3 Pre Processing

Image to image registration was conducted using ENVI 5’s automated tie point analysis workflow (Exelis Visual Information Solutions 2013). Mean pixel error was verified to be within less than half a pixel for both RapidEye and Landsat image pairs. Simple atmospheric correction was conducted by subtracting the darkest pixel value from deep water bodies in all four images (Chavez 1996). Lastly, image to image radiometric normalization was conducted using a multivariate alteration detection algorithm (MAD) described by Canty et al. (2004).

3.3.4 Derivation of Vegetation Indices

A survey of the literature was conducted to determine an appropriate selection of common vegetation indices used to detect fires. The Enhanced Vegetation Index (EVI), the Soil Adjusted Vegetation Index (SAVI), and the Normalized Difference Vegetation Index (NDVI) were selected because they were applicable to both RapidEye and Landsat sensors. In addition, the NBR (only applicable to Landsat) was also used due to its proven ability to detect fires and
predestinated burn severity classes (Key and Benson 2006). All of the indices, except for the NBR, take advantage of changes in reflectance exhibited in the red and NIR portions of the electromagnetic spectrum following fire. The NBR emphasizes the change in reflectance caused by combustion of forest fuels from two of the least correlated bands, the NIR and the short-wave infrared (SWIR) (López García and Caselles, 1991). Spectral bands in the SWIR and the MIR regions of the electromagnetic spectrum have been shown to exhibit opposing responses following fire. In general reflectance in the NIR regions tends to decrease (Sunar and Özkan, 2001) while MIR reflectance increases (van Watendonk et al. 2004). Although the RapidEye sensor does not provide a MIR band to derive and NBR or similar index, Smith et al. (2005) suggested NBR may not be appropriate for finer spatial resolution imagery due to smaller pixels being influenced by the presence of ash, resulting in higher reflectance values. Table 3.2 provides a summary of the vegetation indices used in this study and their respective formulas.

### Table 3.2: Common vegetation indices and their formulas

<table>
<thead>
<tr>
<th>Index Name</th>
<th>Formula</th>
<th>Applicable to</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enhanced Vegetation Index (EVI)</td>
<td>(NIR - Red) / (NIR + Red)</td>
<td>Landsat and RapidEye</td>
<td>Huete et al. 1994</td>
</tr>
<tr>
<td>Normalized Burn Ratio (NBR)</td>
<td>(NIR - SWIR) / (NIR + SWIR)</td>
<td>Landsat</td>
<td>Miller and Thode 2007</td>
</tr>
<tr>
<td>Normalized Difference Vegetation Index (NDVI)</td>
<td>(NIR - Red) / (NIR + Red)</td>
<td>Landsat and RapidEye</td>
<td>Colwell 1974</td>
</tr>
<tr>
<td>Soil Adjusted Vegetation Index (SAVI)</td>
<td>(NIR – Red) / (NIR + Red + L) *(1+L)</td>
<td>Landsat and RapidEye</td>
<td>Huete 1988</td>
</tr>
</tbody>
</table>
For each calculated index and difference image was created by subtracting the T$_2$ image (post-fire) from the T$_1$ (pre-fire) images. The detection of change due to fire was then conducted on four difference images from RapidEye and four difference images from Landsat.

### 3.3.5 Exploring Spatial Variability and Image Semi-variance
An analysis of semi-variance across the study area was undertaken to analyze the spatial and spectral variability for both the RapidEye and Landsat sensors (Johansen et al., 2007). Metrics estimated from semi-variograms can aid in the determination of a suite of spatial and ecological mapping concerns, including image element size and image minimum mapping unit (MMU) (Johansen et al. 2007), while the shape of the semi-variogram can be used to determine optimal distances between sample locations, removing the effects of spatial autocorrelation (Curran 1988, Trietz and Howarth 2000). For a detailed review of applications of semi-variance analyses using remote sensing see Naimi et al. (2011). In order to compute semi-variograms from the imagery, we used R package USDM (Version 1.1-12) to calculate semi-variance on the entire suite of VBNWA images (Naimi 2014). Lag distances were specified as the respective Landsat and RapidEye cell lengths (30m and 5m respectively).

### 3.3.6 Relating field data to Vegetation Indices
The mapped tree data was overlaid with difference image raster data using a GIS and regression analysis was conducted between the SBI and spatially corresponding pixel values. For the Landsat imagery it was necessary to average SBI measures for Landsat pixels containing multiple mapped trees; this was not necessary for RapidEye imagery since no trees occupied the same pixel. Because of potential geo-locational error associated with the GPS ground location data and the remotely sensed images a low pass, smoothing, filter with a 3 by 3 kernel was applied prior to the derivation of the vegetation indices. Pixels from filtered vegetation index
difference images were then extracted to shapefile point features and subjected to regression analysis.

To provide an indication of the efficacy of each vegetation indices’ ability to differentiate fire severity, ground estimates of crown scorch were divided into three arbitrary classes (0-33%, 33-66%, and 66-100% scorch). Analysis of variance was used to test for differences between these classes.

Burn severity classes were adapted from Key and Benson’s (2005) description to map burn severity throughout the study area. The dNBR severity classes from Landsat imagery were sampled using the Zonal Statistics tool provided in ArcMAP’s Spatial Analyst toolbox and applied to overlying RapidEye pixels (ESRI 2014).

Fuel consumption data gathered along transects was used to estimate woody surface fuel biomass consumed for each severity class. Field estimates of consumed woody surface fuels were stratified by RapidEye severity classes to provide an average measure of fuel consumption by class. Estimated biomass consumed was extrapolated to estimate surface fuels consumed throughout the entire burn area.

### 3.4 Results:

Semi-variograms comparing spectral variability between RapidEye and Landsat imagery revealed that Landsat had less overall variability compared to RapidEye (Figure 3.3). The RapidEye band semi-variograms revealed a definitive sill around 400m, while the Landsat band semi-variograms did not have a definitive shape or sill. The abrupt curve depicted by the RapidEye semi-variogram at between 0 and 30 meters provides an indicator of the spatial
variability of the stand due to its open structural composition. The lack of a sill on the Landsat imagery indicates at 30m spatial resolution this finer spatial detail is not captured.

Stratified estimates of crown scorch demonstrated that both sensors were able to differentiate crown scorch levels; however some indices performed better than others (Figure 3.4). The mean SAVI values provided the best differentiation of crown scorch classes for both the RapidEye and Landsat sensors, suggesting that SAVI would be the best vegetation index for mapping fire severity. Analysis of variance among crown scorch classes revealed that all stratified canopy estimates exhibited significant differences (p < 0.05). A post-hoc Tukey HSD test revealed significant differences between crown all scorch classes except RapidEye dNDVI and Landsat

Figure 3.3 Semi-variograms comparing RapidEye and Landsat imagery for visible and near infrared bands
dNBR which resulted in no significant differences between the low and medium crown scorch categories (p > 0.05).

Figure 3.4 Comparison of crown scorch severity estimates for Landsat and RapidEye Sensors. * indicates indices are not comparable across sensors.

The resulting coefficients of determination ($R^2$) for regression analysis between SBI and vegetation indices are provided in Figure 3.5. For both Landsat and RapidEye the SAVI index provided the best fit with the SBI.
Figure 3.5: Comparisons of Coefficients of Determination ($R^2$) for correlations between SBI and vegetation indices derived from Landsat and RapidEye Imagery.

Figure 3.6 provides scatter plots of the best fit between the RapidEye and Landsat SAVI indices. In the case of Landsat imagery the 30m data resulted in field sample locations averaged by pixel, thereby reducing point samples from 116 to 26 for the Landsat regression.
A map of fire severity is provided in Figure 3.7. Due to the relatively low severity of the fire, only ‘low’ and ‘moderate’ severity classes were interpreted using the dNBR classes described by Key and Benson (2006). Furthermore, since much of the fire appears to have burned under the canopy; only 2 of the 40 ha mapped were classified by moderate severity burn. In addition to the ‘low severity’ class derived from the dNBR values, it was necessary to add an additional ‘grass burn’ severity class, with a threshold calculated by the median value between ‘no-change’ and ‘low severity’ burn classes.
Figure 3.7 Map of dSAVI fire severity classes using transferred dNBR classes described by Key and Benson (2006)
Estimated fire severity classes from SAVI are provided in Table 3.3. The relative percentages of woody surface fuels consumed increased with severity class; however several consumed pieces of wood (n = 21) occurred in areas where no change was detected. This resulted in an estimated 19.3 ± 5.9% of fuels consumed within the no change class.

Table 3.3 Estimate of woody surface fuels consumed grouped by burn severity class, error is estimated as standard error of the mean.

<table>
<thead>
<tr>
<th>Class</th>
<th>RapidEye dSAVI Values</th>
<th>% LWD Fuels Consumed</th>
<th>Area Mapped (ha)</th>
<th>Biomass Consumed by class (Mg/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Change</td>
<td>0.000 to 0.022</td>
<td>19.3 ± 5.9</td>
<td>12.6</td>
<td>3.38 ± 1.03</td>
</tr>
<tr>
<td>Grass Burn</td>
<td>0.022 to 0.027</td>
<td>33.3 ± 8.6</td>
<td>16.5</td>
<td>5.84 ± 1.51</td>
</tr>
<tr>
<td>Low</td>
<td>0.027 to 0.034</td>
<td>52.0 ± 6.2</td>
<td>9.3</td>
<td>9.12 ± 1.09</td>
</tr>
<tr>
<td>Moderate</td>
<td>0.034 to 0.060</td>
<td>66.9 ± 10.5</td>
<td>2.1</td>
<td>11.72 ± 1.84</td>
</tr>
</tbody>
</table>

### 3.5 Discussion

Improving accuracy of carbon budget models through remote sensing is an ever-increasing focus of research. With forests presenting a potential sink and source of atmospheric carbon, detailed forest monitoring will become increasingly important for scientists and policy makers. Although forests are considered a net sink at the global scale, carbon fluxes have been shown to vary dramatically by region (Pan et al. 2011). Estimating the contribution of individual forest attributes, such as the combustion of live crowns and woody fuels, to specific carbon pools is also a challenge for carbon monitoring (Vaillant et al. 2013).

#### 3.5.1 Assessment of Spatial Variability

As expected, semi-variogram analysis of both post-burn images revealed a greater degree of spatial detail within the RapidEye imagery. The ability to resolve finer scale spatial features
using RapidEye imagery, coupled with the potential ability to detect damage to individual tree crowns, could provide benefits to fine scale disturbance mapping projects. Although the effective range for both sensors was achieved at a distance of approximately 400 meters (Figure 3.3), the abrupt partial sill in the RapidEye semi-variograms indicates fine-scale stand attributes such as gaps between individual trees can be detected and offers advantages for fine-scale ecological applications (Johansen and Phinn, 2006). This large partial sill was depicted in the RapidEye imagery between approximately 5 and 30 meters lag, a level of spatial detail not available in the Landsat imagery. This also indicates potential for RapidEye imagery to be used to map fires, which leave behind a complex burn patterns on the landscape (Kachmar and Sanchez-Azofeifa 2006), particularly in relatively low-severity fires.

3.5.2 Relating Field Data to Vegetation Indices
Boxplots differentiating crown scorch classes yielded similar results for comparable indices across sensors (EVI, NDVI, and SAVI). Although ANOVA tests conducted on crown scorch classes revealed significant differences between classes for all indices from RapidEye and Landsat, post-hoc Tukey’s HSD revealed that RapidEye dNDVI and Landsat dNBR were unable to differentiate between low and medium crown scorch classes; a possible indication of these indices’ insensitivity to minor changes in vegetation damage and condition (Epting et al. 2005).

RapidEye’s red-edge band produced unexpected results compared to the other indices with change vectors decreasing along the crown scorch severity gradient. Interestingly Ramoelo et al. (2012) found that RapidEye’s red-edge band could be used to improve foliar nitrogen estimates when used in tandem with other vegetation indices, suggesting that the red-edge band may not be particularly useful as a single index. It should also be noted that the red-edge was the only single band index used in our analysis, (i.e. not a ratio of two or more bands).
Regression analysis revealed that the dSAVI index provided the highest $R^2$ value of all indices for both RapidEye and Landsat. This relationship is not surprising, as the SAVI index was developed to account for inherent soil reflectance from below the canopy (Huete 1988). The ability of the SAVI to shift the relationship between reflectance emitted in the NIR and red regions of the electromagnetic spectrum using the constant ‘L’ appears to have accounted for proportion of the increased reflectance caused by soil and relatively open stand structure, characteristic of the study area (FLNRO 2014). Results may have varied if the study area exhibited a higher level of crown closure.

Apart from the single red-edge band, dNBR provided a relatively poor correlation between the SBI, likely due to low severity of the fire and little overall change to stand structure. Although Epting et al. (2005) found a higher correlation was achieved in a relatively closed stand with the dNBR index, the forest stands in their study experienced more severe stand damage and displayed a relatively higher crown closure, suggesting that scalar, structural, and severity attributes may influence stand correlation between SBI and indices. Based on the results of our analysis, we do not recommend using dNBR to map low-severity fires.

### 3.5.3 Estimation of Sub-canopy Fuel Consumption

Adapting dNBR severity classes to dSAVI produced four classes ranging from ‘grass-burn’ (no apparent canopy damage, but evidence of spectral changes to the sub-canopy) to ‘moderate severity’ (Figure 3.7). Estimates of fuels consumed by severity class revealed that $19.3 \pm 5.9\%$ of fuels were consumed in the ‘no-change’ class, a potential challenge when mapping low severity fires. This estimate of fuels consumed by the no-change class was likely attributed to four potential factors as follows: (1) the inherent low-severity nature of the fire; (2) the T2 image being acquired 19 days after the later T1 anniversary date; (3) substantially different amounts of
precipitation leading prior to the acquisition of the imagery with T2 being markedly drier than T1 or (4) issues associated with transferring dNBR derived severity classes to other types of vegetation indices. Meteorological data from the nearby Penticton weather station revealed that spring 2013 was also relatively dry (Climate Canada); potentially affecting the estimated severity of the mapped burn classes (van Wagendonk et al. 2004). In the grass, low, and medium burn severity classes the fire consumed 33.3 ± 8.6%, 52.0 ± 6.2%, and 66.9 ± 10.5% of woody fuels, respectively.

Estimates of woody surface fuels’ contribution to forest carbon pools can range from 5-26% (Muller and Lui 1991), and, therefore, should be considered when assessing forest management objectives. In a more complex analysis, Smith and Hudak (2005) used aerial photography and Landsat imagery to estimate the woody surface consumed by fire by estimating the area of white ash within imagery. However, white ash is only formed from the full combustion of woody fuels under very high heat and was present in negligible quantities in our study area. In our medium severity class, we estimated 66.9 ± 10.5% of woody surface fuels were consumed, which is comparable to consumption estimates in similar ecosystems (Harington 1987, Hille and Stephens 2005). The extrapolated estimates of total wood fuel biomass consumed were comparable to estimates presented in other studies (e.g. Hille and Stephens 2005). In total, an estimated 247.7 ± 51.8 Mg of woody surface fuels were consumed. Comparing our estimates to other studies we find that our consumed fuels in the VBNWA to be similar; for example Vaillant et al. (2013) found prescribed burn to have reduced woody surface fuels by 10 Mg ha-1 in a managed forest in California, our highest severity class (moderate) predicted a surface woody fuel loss of 11.7 Mg ha-1.
3.5.4 Monitoring Implications
Although our study demonstrated a relatively simple approach to estimate the amount of consumed large woody surface fuels, the ability to achieve fine level of spatial detail offers valuable advantages to assess changes in ecosystems at a scale relevant to management.

Criticism of severity classes applied to vegetation indices are generally founded on the basis that metrics of severity attributed to remotely sensed indices do not directly correlate to empirical changes in vegetation and biomass consumption (Lentile et al. 2005). In addition, transferability of severity classes across ecosystems presents several challenges to designating universal severity metrics (Jain and Graham 2004). While optical remote sensing can provide good estimation of spatial distribution of vegetation types and disturbances, optical imagery still must be supplemented by vertical structural attributes in order to achieve accurate estimates of carbon stocks (Wulder et al. 2009). Metrics derived from other sensors capable of resolving structural attributes such as Light Detection and Ranging (LiDAR) may be fused with optical indices to provide detailed inventories of change due to disturbances (Bolton et al. 2013), however routine monitoring using LiDAR is generally considered expensive and beyond the scope of most management budgets.

As strategies for carbon monitoring become increasingly applied to achieve forest management objectives, frameworks will inevitably develop to assess and actively monitor wildfires. Currently active monitoring of fires relies on very coarse resolution satellites to detect changes (resolution of 1 km²) (Miettinen et al. 2013); however, RapidEye could augment active fire monitoring given its high spatial and temporal resolution. Sensors such as RapidEye and other fine-scale remotely sensed imagery could provide advantages to estimating forest carbon in reserves or to provide detailed mapping of specific burn areas. Furthermore, since above ground
forest carbon can change quickly as the result of different management regimes (Hines et al. 2010), the fine temporal resolution of RapidEye could be used to assess the immediate effects of management treatments and monitor their outcomes over time.

3.6 Conclusion

The greater spatial variability provided by the RapidEye data demonstrated potential for fine scale mapping of burn damage throughout the study area. Overall RapidEye did not appear to correlate any better with the ground data than the averaged SBI estimates correlated with the Landsat data. Inherent seasonal differences may have influenced our ‘grass burn’ severity class, potentially exaggerating the extent of that category and thus over-representing LWD consumed for the grass-burn class. The temporal availability of RapidEye provided an advantage over Landsat, with several cloud free images readily available covering the research area. Image analysis suggests that RapidEye was able to provide a greater detail of spatial patterns and objects compared to Landsat. The estimation of burn severity classes in this research simply provided an empirical methodology for estimating consumption of large wood fuels weightings as well as burn severity classes should be implemented on a site-by-site basis, but should have some grounding in empirical vegetation damage. Cost considerations regarding the specific level of detail should therefore be assessed prior to considering the acquisition of RapidEye imagery over the free, but less detailed Landsat imagery. Practical applications could include park and reserve management designs and planning, assessment of forest disturbances, and monitoring sensitive areas.
CONCLUSION

The overarching goal of this study was to assess the ability of the RapidEye constellation to detect forest disturbances in British Columbia. Optical remote sensing has been consistently proven in its ability to assess stand replacing disturbances (Achard et al. 2002; Kasischke and Turetsky 2006; Healey et al. 2005; Maskek et al. 2008), however assessment of non-stand replacing and structural aspects of disturbance using optical imagery remain a challenge (Kimes et al. 2006; Lefsky et al. 2002; Frokling et al. 2009). Medium and low-spatial resolution sensors such as Landsat and MODIS have demonstrated accurate identification of stand replacing disturbances for decades; yet achieving metrics other than presence/absence of disturbance has proven difficult using optical imagery alone (Wulder et al. 2009). Although technologies such as Light Detection and Ranging (LiDAR) can provide precise estimates of structural forest attributes, these technologies remain limited due to high operational costs (Ma et al. 2014) and are not considered feasible for routine forest monitoring.

The results of this study demonstrate that RapidEye offers potential advantages to assess both stand and non-stand replacing disturbance over other sensors. In addition, the relatively fine spatial resolution and frequent image acquisition may offer many advantages to improve routine monitoring of forest disturbances.

The first research question examined the potential of RapidEye to assess the presences/absence of stand-replacing disturbance, while the second study addressed finer-scale disturbance metrics after a single, non-stand-replacing fire. Both studies highlight the sensors’ ability to assess stand replacing and non-stand-replacing disturbances at yearly intervals, a timeframe relevant to meet the needs of most forest management initiatives. Although the research was conducted in a British Columbian context, the overarching research is intended to aid in forest inventory
globally and support a variety of applications including improving forest inventories, prioritizing conservation efforts, ecological mapping and monitoring, and carbon accounting. We hope that results of this study will aid in the ongoing objectives associated with broad-scale forest management and will be adapted to accommodate a variety of research and monitoring initiatives.

4.1 Key Findings

In Chapter 2 a method was developed for mapping the extent of stand replacing disturbances over a set of diverse forest types in British Columbia. By adapting the methods of Healey et al. (2005) a modified disturbance index was developed specifically for RapidEye imagery. A simple threshold was applied to the modified disturbance index to differentiate stand replacing disturbances and unchanged land. The modified disturbance index and simple threshold technique was able to identify stand replacing disturbances at an accuracy of 92.64 ± 0.15% using forest inventory data and 96.91 ± 1.16% using an independently verified dataset. It was also noted that classification of disturbance could be improved if a more sensitive cloud identification technique had been employed. Furthermore, the seven 25 X 25 km RapidEye tiles selected for the study were all available as image pairs with <10% cloud cover and within ±20 days of each other’s respective anniversary date, a level of temporal detail that is largely unavailable from other high spatial resolution sensors. The high classification accuracy coupled with the extensive image archive, and potential to capture daily imagery over a given region suggested the RapidEye constellation could aid in the ongoing monitoring of disturbances such as wildfire, or illegal logging activity, especially in regions where access is difficult or unfeasible (Grainger and Obersteiner, 2011).
In Chapter 3 the potential of RapidEye to assess the condition of vegetation following a low-severity, non-stand-replacing burn in a dry western Canadian forest was explored. In this study metrics derived from both Landsat (TM and OLI) and RapidEye imagery were compared on their ability to detect fine-scale disturbance attributes. Estimates of tree damage and consumption of woody surface fuels were used to compare effectiveness of vegetation indices derived from RapidEye and Landsat.

Analysis of the spatial variability provided by the post-fire imagery revealed that RapidEye was able to achieve spatial detail capable of resolving damage on an individual tree basis. This level of detail occurred between 5 and 30 meters, and was therefore unattainable using Landsat with its 30 meter resolution. Regression analysis revealed significant relationships between all vegetation indices and the derived Simple Burn Index (SBI) -a weighted measure of collated burn damage. The SBI and Soil Adjusted Vegetation Index (SAVI) provided the best fit of regression for both Landsat and RapidEye. Although Landsat was ultimately able to provide a better fit of regression (SAVI, $R^2 = 0.56$) from mean aggregated SBI scores, RapidEye imagery produced a comparable coefficient of determination (SAVI, $R^2 = 0.51$) using SBI observations for individual trees. The estimation of consumed woody surface fuels classes from derived spectral classes also exposed the additional detail provided by RapidEye and demonstrated the sensors’ potential to quantify specific ground-level attributes, a detail often overlooked in burn severity studies (Lentile et al. 2006). In addition estimates of consumed woody surface fuels were comparable to other studies using more detailed and extensive field measures (Harington 1987; Hille and Stephens 2005; Vaillant et al. 2013). The results of this study demonstrate the ability of RapidEye to map fine-scale attributes associated with ecological change caused by fire.
4.2 Future Work

Remote sensing technologies will become increasingly used to address multitude of land use concerns. To meet the demands of a growing industry and research community it is necessary to develop remote sensing-derived products and applications to support a range of disciplines. RapidEye’s ability to capture many images per year over a given area makes it an ideal candidate for strategic monitoring of forest resources. This research has clearly demonstrated that potential of RapideEye to augment forest inventories throughout a variety of forest types. Based on the findings of this research the we recommend: (1) exploring of sensor automation to monitor forest disturbances using satellite constellations should be explored (2); derived disturbance indices from RapidEye across various biomes be assessed, and finally (3) the integration of RapidEye with active sensors, particularly LiDAR, should be investigated.

Satellite constellations provide opportunities for near real-time mapping of disturbance and other abrupt land change events. Full or partial automation of land cover change is an emerging field of study that will arguably lead to enhanced decision making, policy, and disaster response (Verbesselt et al. 2012). Real-time and near real-time frameworks are already in place to detect large disturbances such as wildfires (Ruminski et al. 2008). However, the sensors used to detect these events are typically mounted on high orbital, geostationary satellites which provide relatively coarse spatial resolution imagery (Zhang et al. 2012). The integration of finer spatial resolution sensors, capable of frequent image acquisition could aid in near-real time mapping of disturbance or natural disasters. Augmenting coarse real-time monitoring frameworks with finer spatial resolution data could potentially aid in natural disaster response and relief efforts.

Assessing RapidEye’s ability to derive universal metrics of disturbance across biomes would inevitably increase the applicability of RapidEye to detect disturbance. Although our initial
detection algorithm was developed using a diverse set of forest types in British Columbia, it would be beneficial to assess the modified disturbance index in other biomes, particularly tropical and broadleaf-dominated forests, which may exhibit different spectral responses than the primarily conifer dominated forests used in this study. Furthermore, standard vegetation indices derived from satellite imagery may vary significantly by biome (Huete et al. 1997). It is therefore recommended that RapidEye’s disturbance detection capabilities be assessed across a diverse range of ecological gradients, particularly broadleaf and tropical forest types.

Finally the integration of RapidEye disturbance detection with non-spectral sensors, capable resolving structural attributes associated with vegetation could be advantageous for quantifying disturbance events. Two dimensional data is inherently limited with respect to resolving structural attributes of vegetation (Wulder et al. 2009). As seen in chapter 3, the variability associated with fine-scale attributes could potentially be improved by adding metrics of structural attributes associated with tree damage. LiDAR, in tandem with satellite imagery has been shown to enhance ecological mapping and modeling application using optical imagery at a range of spatial resolutions (Bolton et al. 2013; Hlakdik et al. 2013). Integrating RapidEye with LiDAR could provide powerful analytical tools aimed at forest inventories, ecological mapping and monitoring, and carbon accounting and should be explored.
REFERENCES


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